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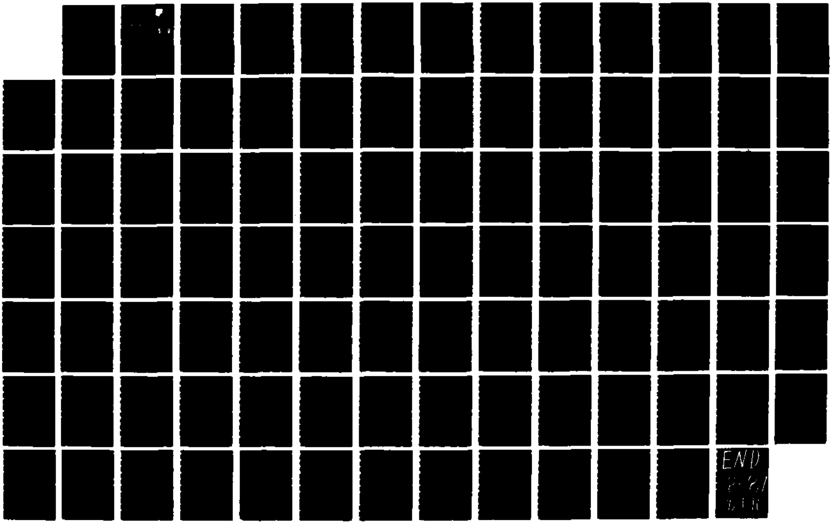

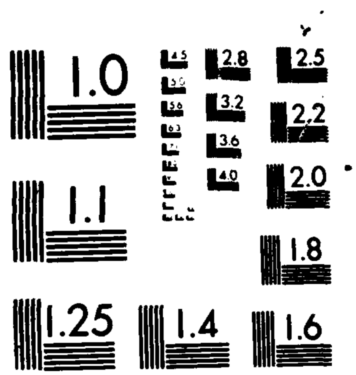

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May 1987

R&M PROGRAM COST DRIVERS

Hughes Aircraft Company

L. E. James, R. R. Wickham and S. J. VanDenBerg

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ROME AIR DEVELOPMENT CENTER
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This report presents the results of a study to establish parametric cost estimating relationships (CER's) for reliability and maintainability program tasks or groups of tasks; and to investigate the feasibility of determining cost-benefit indices. The specific tasks are defined in MIL-STD-785 and MIL-STD-470. The CER's were developed using multiple linear regression analysis (MLR) based on data from 23 projects of varying size and complexity.

The cost-benefit investigation determined that the MLR techniques were also applicable to developing models for estimating MTBF gain as a measure of benefit.

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FOREWORD

This report presents the results of a study to establish parametric cost estimating relationships (CER's) for reliability and maintainability program tasks or groups of tasks, and to investigate the feasibility of determining cost-benefit indices. The specific tasks are as defined in MIL-STD-785 and MIL-STD-470. The CER's developed herein were derived using a data base large enough to provide statistically significant results. Labor hours to accomplish specific R&M tasks (or groups of tasks) are estimated based on program characteristics which require information that is readily available in the planning stages. With sufficient program information, these CER's can be used as pricing standards for the associated R&M tasks when applied under the stated data base constraints. Multiple linear regression analysis (MLR) was the basic tool used to develop the CER's, and the data base description, detailed analysis, and examples of application are presented in this report.

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S.0 EXECUTIVE SUMMARY

S.1 Purpose & Scope of Study

The purpose of this study was two-fold: (1) the development of models for estimating the cost of Reliability and Maintainability (R&M) program tasks and (2) the determination of the feasibility of developing cost/benefit ratios for each such task or set of tasks.

A data base consisting of historical project file information was established from which a large set of statistically valid models for estimating R&M task labor was developed. Military electronics projects of varying size and complexity were provided by the Hughes data base. The cost data consisted of approximately 40,000 weekly labor records which were categorized by R&M tasks similar to those defined in MIL-STD's 785 and 470.

To determine tangible benefits from conducting R/M tasks, four approaches were investigated. These were: (1) direct assessment of the benefit or gain, (2) assessment by case study, (3) assessment by expert opinion, and (4) regression analysis of observed benefits with R/M task application characteristics. Several of these approaches are recommended for future study.

S.2 Overview of Study Results

A method of estimating R&M task cost (i.e., labor hours) based on data that is normally available during the early program planning stages has been developed. The method consists of a set of seven cost-estimating-relationships (CER's); one general relationship for estimating total R/M program costs and six relationships specific to individual R/M task areas. These CER's provide a tool for comparing alternate R&M program costs (i.e., different tailorings of MIL-STDs 785 and 470), and give rules-of-thumb for estimating what a specific R&M program should cost under stated conditions. The CER's were derived from data on the projects using multiple linear regression (MLR) techniques. Many of the MIL-STD 785 and 470 tasks required grouping in order to provide sufficient data to generate statistically significant CER's. The data base and study results are summarized in the following paragraphs with details provided in the body of the report.

The weekly labor record format used in the data base had separate codes for each of the MIL-STD-785 and 470 tasks which could be computer sorted by project. A "point" in the data base consists of a project identifier, task description data for each R/M task required by the program, and the corresponding labor appenditures for each task. In many cases, significant statistical correlations were often achieved only when R-labor charges were combined with M-labor charges for the same type of tasks, such as the preparation of program plans. Similarly, higher correlation was also achieved when like tasks were combined; for example, the FRACAS effort (Task 104) combines naturally with Failure Review Board effort (Task 105). Moreover, a number of R&M tasks are classified under the general heading of project management. These include such tasks as administration of the R&M programs by the lead engineer (not identified as a MIL-STD task), subcontractor/vendor monitoring and control (Task 102), and participation in program reviews (Task 103).

Twenty-three Hughes projects in various stages of development, production, and of field usage were surveyed and determined to have sufficient data history to be included in the data base. Specific data points used to develop the models (i.e., labor hours and associated systems and task application characteristics) were obtained from three sources: (1) computerized historical labor records on specific R&M tasks that had been maintained across each of the projects; (2) equipment/descriptive data from available project files; and (3) interviews with the reliability and maintainability engineers responsible for conducting the various R/M tasks.

Cost estimating relationships (CER's) were developed based on standard multiple linear regression (MLR) techniques. The fitting procedure ensured inclusion of all variables which had predicative importance. At every stage of the CER development, engineers experienced in pricing R&M tasks as well as the project responsible R/M engineers were consulted to ensure that the estimating techniques were reasonable, plausible, and usable during early task planning phases.

A single CER was developed to estimate the total R/M program costs. The model was designed for ease of use while retaining a sufficient number of task description parameters to provide reasonable estimates. More accurate models of individual R/M tasks or groups of tasks were also developed, and these CER's are recommended whenever the appropriate level of project detail is available to meet the input data requirements of the model.

The CER for total R/M program costs is described in Section 1.3 of this report, and the CER's for each R/M task area are described in Section 3.0. Within Section 3.0, each CER is completely documented. The information on each CER includes: (1) a definition of the input data requirements with ranges of application for each of the model parameters; (2) detailed CER model description including statistical fit information and examples of how to apply the models; and (3) tabled values of selected parameter ranges using the model with the "best-fit" statistics.

The study data base used to generate the CER's can be expanded by adding project data points to the input data given in Appendix B, adjusting the CER coefficients through regression, and adhering to the constraints on the variables given under the appropriate subsections of 3.0.

S.3 Recommendations for Future Study

The primary objective intended for this study was to establish CER's for the R/M program tasks. To determine the benefits gained from the expenditures on these R/M tasks is a difficult but natural follow-on study. The investigation conducted in this study to determine the feasibility of deriving measurable benefits from conducting selected R/M Tasks (see Section 4.0) indicated that the multiple linear regression (MLR) analysis approach is the most promising. The MLR approach would be consistent with the CER development used in this study and has the advantage of being the most objective of the approaches investigated. The development of a benefits model using MLR, however, would require a much larger sample size. A minimum sample size of 30 systems is recommended. To provide supporting information for this development, it is also recommended that industry questionnaires and case studies, as referenced in this report, be included in any future effort.

In addition, the life cycle benefits of an R/M program should be considered. Improvements in hardware R/M resulting from the implementation of an R/M program manifest themselves as cost savings derived in reduced spares and maintenance manpower or in increased operational readiness and could have a substantial impact over the life of the system. Only a small gain in actual MTBF per system, for example, would result in a large life cycle cost reduction in the maintenance support areas for a large deployment of such systems.

1.0 SUMMARY OF STUDY RESULTS

1.1 Introduction.

1.1.1 Purpose. The objectives of this study were the development of quantitative or heuristic models for estimating on an individual or composite task basis, the cost of Reliability and Maintainability (R&M) programs for electronic equipment and the determination of the feasibility of developing cost/benefit ratios for each such task or set of tasks.

1.1.2 Background. MIL-STD-785 and MIL-STD-470 define the necessary R&M activities needed to ensure equipment/system designs comply with specified Government requirements. Currently, problems exist in both (1) defining the cost of R&M programs in terms of the individual program tasks and (2) determining the cost/benefit associated with each task. (In other words, how much reliability or maintainability can a given task buy?) Previous models, guidelines, data and analyses are no longer appropriate. Technology has changed and emphasis in this area has shifted to the use of tailored, as opposed to blanket, R&M programs. Both Government and industry require information and guidance such that visibility and insight may be gained as to the cost ramifications and cost effectiveness of R&M programs.

1.1.3 General Approach to the Study. An extensive in-house data base was accessed in order to establish a large set of statistically valid models for estimating R&M task labor. A minimum of eight different military equipment/system programs were required by the study Statement of Work but it was believed that a much larger data base was needed to provide a statistically valid result. A total of 23 projects of varying size and complexity were provided by the Hughes data base. The data base consisted of approximately 40,000 weekly labor records which were categorized by R&M task. Reliability engineers within the Systems Effectiveness laboratory reviewed the data and researched any anomalies discovered in the data. A multiple linear regression approach was used on a set of key system and task application variables.

1.2 R/M Cost Models, Ground Rules and Assumptions. In determining effective cost-estimating-relationships (CER's), it is essential to ensure that all variables which have a significant influence on R&M task cost (i.e., labor hours) are included in the relationship. Moveover, the input data needed to use the CER's should consist of information typically available prior to the performance of the associated R&M tasks.

The general forms of the CER's are given by:

$$(1.2\text{-}1)\quad T = C_o + C_1 Z_1 + C_2 Z_2 + \dots + C_p Z_p \text{ , and}$$

$$(1.2\text{-}2)\quad T = C_o Z_1^{C_1} Z_2^{C_2} \cdots Z_p^{C_p}$$

where T is the dependent cost variable expressed in labor hours to perform the specified R/M task or set of tasks; the Z_i are the independent variables representing system and task application characteristics, or functions thereof, which have significant correlation with T; and the C_i are constants of the CER determined by the regression fit. Equation (1.2-2) is not linear in the independent variables Z_i and, therefore, must be transformed to linear form before MLR techniques can be applied. Taking the natural logarithms of (1.2-2), results in the following linear form:

(1.2-3) $\ln T = \ln C_0 + C_1 \ln Z_1 + C_2 \ln Z_2 + \cdots + C_p \ln Z_p$

All discussions in this report referring to MLR models, fit characteristics (i.e., R^2, regression error etc.) and associated assumptions pertain to equations (1.2-1) and (1.2-3). A detailed discussion of the MLR model development process is provided in Appendix A. A brief summary of the model assumptions and ground rules is given below:

1. The dependent variable in (1.2-1) or (1.2-3) is a linear combination of p independent variables. In matrix notation the MLR model is represented in the form:

   $Y = XB + e$

   where:

   Y = (n x 1) vector of observations of the dependent variable; $(T_1, T_2, \ldots, T_n)$ for (1.2-1) and $(\ln T_1, \ln T_2, \ldots, \ln T_n)$ for (1.2-3).
   X = (n x p) matrix of observations of the independent variables; $X_{ij} = Z_{ij}$ for (1.2-1) and $X_{ij} = \ln Z_{ij}$ for (1.2-3), $1 \leq i \leq n$ and $1 \leq j \leq p$.
   B = (p x 1) vector of constants (CER coefficients) to be estimated.
   e = (n x 1) vector of errors.

2. The elements e_i, $1 \leq i \leq n$, of the vector e represent values of a normally distributed random variable.

3. E(e) = (o) and Var (e) = I , where I is the identity matrix, so that the elements of e are assumed to be uncorrelated.

Table 1.2-1 identifies the CER's and associated MIL-STD-785/470 task (or group of tasks) and provides some general statistics on how well the model fits observed data. R^2 values greater than 0.9 are generally considered excellent fits. The last column references the report paragraph which defines the input data requirements, the CER model, and example applications. A summary-level model was also developed which estimates the total labor hours expended in an R/M program (see 1.3).

Although the weekly labor record format had separate codes for each of the MIL-STD-785 and 470 tasks, significant correlations were often achieved only when R-labor charges were combined with M-labor charges for the same type of tasks (e.g., Tasks 101, 201, 202 and 203). Similarly, higher correlation was also achieved when like tasks were combined (e.g., 104 combined with 105, 201 combined with 202 and 301, 303 and 304 combined).

A number of R&M tasks are classified under the general heading of project management (see Table 1.2-1). These tasks include: administration of the R&M programs by the lead engineer; subcontractor/vendor monitoring and control (Task 102); participation in program reviews (Task 103); identification and controls for reliability-critical items (Task 208); training of newly assigned R/M engineers; and general R&M

support to the project systems and design engineers not covered by other R&M tasks. For the systems in the data base, project management accounted for approximately 16% of the total R&M task effort.

Parts programs (Task 207) can have a significant cost impact. This is especially the case with high reliability state-of-the-art designs where the potential for large numbers of non-standard parts exists. However, project-related labor records for implementing and conducting a parts program were not maintained in sufficient detail to develop a CER. General rules-of-thumb based on Hughes standard policy on selection control for a parts program in accordance with MIL-STD-965, Procedure 1, are given below:

a.	Program Plan Preparation	80-120 hours
b.	Non-standard parts justification submittal and follow-up	5-8 hours per part
c.	Specification preparation (for non-standard parts procurement)	32-48 hours per part

If special reliability screening is employed to upgrade a non-standard part, the recurring test cost could add 2 to 5 dollars (1986) to the price of a complex integrated circuit. Procedure 2 of MIL-STD-965 would add the cost of the parts control board which is dependent on how often the board convenes, location, etc.

The remaining MIL-STD-785 and 470 tasks are either included in several of the tasks modeled or had insufficient data as noted in Table 1.2-1.

1.3 General R/M Cost Model. A single overall CER was developed to estimate the total R/M program costs (i.e., as defined in Section 3.0). The model was designed to be easy to use during the early R/M program planning stages while retaining enough R/M task descriptive parameters to provide reasonable estimates.

For the derivation of this model, task information from each project in the data base was assembled into a single data set. Tasks not performed on particular projects have corresponding entries equal to zero. This yielded a data set with 23 projects in which one or more MIL-STD-785/470 tasks were performed. The descriptions of the program factors (independent variables) are contained in the appropriate sub-section of Section 3.0.

There were several considerations when exploring the form of the model: ease of use and consistency of estimates were foremost. Simply summing the results of the individual models produced good estimates but an unwieldly equation. This general form was retained but exponents were simplified and parameters were deleted whenever the fit did not suffer appreciably. The MLR program output can be found in Table B.7.2-7. An R^2 value of 0.85 was achieved for a model with only one descriptor for most of the R/M tasks. The final CER is given below, where each term in the equation corresponds to an R/M task or set of tasks as indicated:

$$T_{R/M} = 2.73\,(NOT)^2 + 8.25\,(DOI)^2 + 4.05\,(MAC)^2\,(NOU) \quad (1.3\text{-}1)$$

$$+ 4.54\,(LOD)^2\,(RF)^2\,(POC) + 17.79\,(NOU') + 182.07\,(HC)$$

$T_{R/M}$	=	Total cost (labor hours) of performing the indicated tasks.
NOT	=	Number of R/M tasks to be conducted. Relates to the task of developing an R/M program plan (Task 101).
DOI	=	Duration of FRACAS implementation (Tasks 104 and 105).
MAC	=	Modeling and Allocation complexity factor for R/M Tasks 201 and 202 (see 3.3.1 for scaling).
NOU	=	Number of unique items in the allocation process (Tasks 201 and 202).
LOD	=	Level of detail of the R/M prediction, Task 203 (see 3.4.1 for scaling).
RF	=	Prediction reporting formality, Task 203 (see 3.4.1 for scaling).
POC	=	Percentage of commercial equipment used in the system, Task 203 (see 3.4.1 for scaling).
NOU'	=	Number of unique items requiring an FMECA (Task 204).
HC	=	Hardware complexity in terms of total electronic part count, Tasks 301, 303 and 304 (see Table 3.2-2 for scaling).

Tasks not performed in a given program are accounted for by substituting zero for the appropriate independent variables. Project management can be included as a 16% factor of the total computed task effort, and a parts program cost (based on procedure 1 of MIL-STD-965) can be added using the above rules-of-thumb (see 1.2).

As an example of use of the above model, Project 204 data is employed (refer to Tables B.6-1 through B.6-6). The pertinent descriptors for the R/M are given below:

NOT	=	0,	LOD	=	3
DOI	=	36,	RF	=	2
MAC	=	1,	POC	=	4
NOU	=	445,	NOU'	=	3
			HC	=	3

Substituting these values into (1.3-1) results in:

$$T_{R/M} = 2.73\,(0) + 8.25\,(36)^2$$

$$+ 4.05\,(1)^2\,(445)$$

$$+ 4.54\,(3)^2\,(2)^2\,(4)$$

$+17.79(3) + 182.07(3)$

$= 13748$ Hours (or 15,948 hours including project management)

The observed number of labor hours in conducting R/M tasks for Project 204 was 12,788 (without project management), a difference of approximately 8% from the estimate.

The simplified model represented in (1.3-1) gives reasonable labor estimates for an R/M program. However, for more accurate estimates of an individual task, one of the models defined in Section 3.0 for that specific task is recommended.

1.4 Investigation of Derived Benefits from R/M Tasks. Four approaches to deriving a means of measuring tangible benefits from conducting R/M tasks were investigated. Section 4.0 provides the details of this investigation and the results are summarized below:

a. Direct assessment of the benefit or gain from performing appropriately grouped R&M tasks requires an inordinate amount of detailed engineering data. In addition, this data is generally too subjective (i.e., as to what portion of a change was due to R/M) and unique to a company's way of doing business to have broad-based applications.

b. Task assessment by case study is a useful, but generic, and often subjective, appraisal of R&M benefits best suited to support more detailed analyses. Six Institute for Defense Analysis (IDA) studies were examined showing the key benefit areas to be: Test-analyze-and-fix (TAAF), FRACAS, worst-case/thermal analyses, stress screening and R-growth. However, the studies did not assign benefits to specific task areas.

c. Task assessment by expert opinion suffers from the same problems as in b., in that the responses to a quantitive survey questionnaire are inadequate for statistical analysis and qualitative questionnaires only provide supportive information.

d. Regression analysis of observed R/M benefits with respect to program and R/M task application characteristics (as established in the CER development) provides an objective result but requires a large sample size. This approach only requires an estimate of the total benefit (as opposed to task-by-task estimate of benefit) and can be compared to other more subjective results for consistency.

TABLE 1.2-1. R/M TASK COST ESTIMATING RELATIONSHIPS
Detailed descriptions and example computations are provided in the referenced paragraphs.

CER Description	MIL-STD-785/470 Task Reference	No. of Data Points	Degrees of Freedom*	R^2 Value*	Comments/ Reference Paragraph
R&M Program Plan	101R/M	10	6	0.97	3.1
Monitor Control of Subcontractor Suppliers	102R/M	-	-	-	Included under R/M project management.
Program Reviews	103R/M	-	-	-	
FRACAS/Failure Review Board	104R/M, 105R	13	8	0.99	3.2
R&M Modeling & Allocations	201R/M,202R/M	8	3	0.95	3.3
R&M Predictions	203R/M	16	10	0.97	3.4
FMECA	204R/M	6	2	0.99	3.5
Sneak Circuit Analysis Maintenance	205R	-	-	-	Insufficient Information
Maintenance Analysis	205M	-	-	-	Included in Tasks 201, 202, 203 and 204
Electronic Parts/ Circuit Tolerance Analysis	206R	-	-	-	Included in 203
Maintenance Design Criteria	206M	-	-	-	Included in 101
Parts Program	207R	-	-	-	Hughes policy on selection and control. (see 1.2) Design guides included in 101.
Preparation of Inputs to the Detailed Maintenance Plan and LSA	207M	-	-	-	Included in 203 and 204

TABLE 1.2-1. R/M TASK COST ESTIMATING RELATIONSHIPS (Continued)

CER Description	MIL-STD-785/470 Task Reference	No. of Data Points	Degrees of Freedom*	R^2 Value*	Comments/ Reference Paragraph
Reliability Critical Items	208R	-	-	-	Included in R/M project management
Effects of Functional Testing, Storage, Packaging, Transportation and Maintenance	209R	—	—	—	No information
Reliability Testing	301, 303, 304	7	3	0.95	3.6
Maintainability Demonstration	301M	—	—	—	Insufficient Information
Reliability Development/Growth Test Program	302R	—	—	—	Included in 104/105

*Using model with best fit.

2.0 DATA BASE DESCRIPTION

2.1 Sources of Data. Thirty-three Hughes systems in various stages of development, production and of field usage were surveyed. Twenty-three of these systems were eventually determined to have sufficient data history to be included in the data base (i.e., valid labor accounting records over the period in which the R/M tasks were conducted). The final data base provides a sufficient size and range in the values of the independent variables so that the CER's will have a wide range of application to different types of systems/equipment. Individual equipment as well as complete systems are contained in the data base representing radar, communications, display and data processing technologies. All data points represent military systems/equipment from USAF, Army and Navy contracts and reflect a wide range of operating environments (G_F, G_M, N_S, A_{UF} and U_{SL} as defined in MIL-HDBK-217).

Specific data points used to develop the models (i.e., labor hours and associated system and task application characteristics) were obtained from: (1) computerized historical R&M tasks labor records that had been maintained across each of the above projects; (2) equipment/descriptive data from available project files; and (3) interviews with the reliability and maintainability engineers responsible for conducting the various R/M tasks. Most of the project descriptive data came from interviews and subsequent follow-ups. In order to maintain uniformity across the project data (i.e., with respect to definitions of variables, scaling of qualitative inputs, general assumptions, etc.), a questionnaire format was developed and filled out during each interview. The input data for each CER is provided in Appendix B by project (see Tables B.6-1 through B.6-6).

2.2 Data Processing Methodology. CER's were developed based on standard multiple linear regression (MLR) techniques. The fitting procedure ensured inclusion of all variables which had predictive importance. Where appropriate, alternate CER's are provided along with a best fitting CER for each task. The alternates have fewer variables requiring input data but do not provide as good an estimate of task cost. Measures of their relative fit (R^2 and F-test values) in comparison to the best equation are provided in the detailed description of each CER (Section 3.0.) At every stage of the CER development, engineers experienced in pricing R&M tasks as well as the responsible R/M engineers were consulted to ensure that the estimating techniques were reasonable, plausible, and usable during early task planning phases. The data processing method is illustrated in Figure 2.2-1 and described below. A more detailed discussion of the analysis tools and evaluation criteria employed in developing the CER's is given in Appendix A.

Starting with a large set of candidate independent variables, a questionnaire was developed which categorized these variables by appropriate R&M tasks. The first "screen" in the process was to eliminate those variables which did not have sufficient data for statistical analysis. The remaining variables were then compiled into the CER data base together with the corresponding R&M task labor hours. The second screen eliminated those independent variables and data points which caused "defects" in the CER:

- Form of CER - The CER was considered defective if one or more independent variables had negative coefficients (e.g., a minor variable had inverse correlation with one or more variables already included at a previous step in the regression).

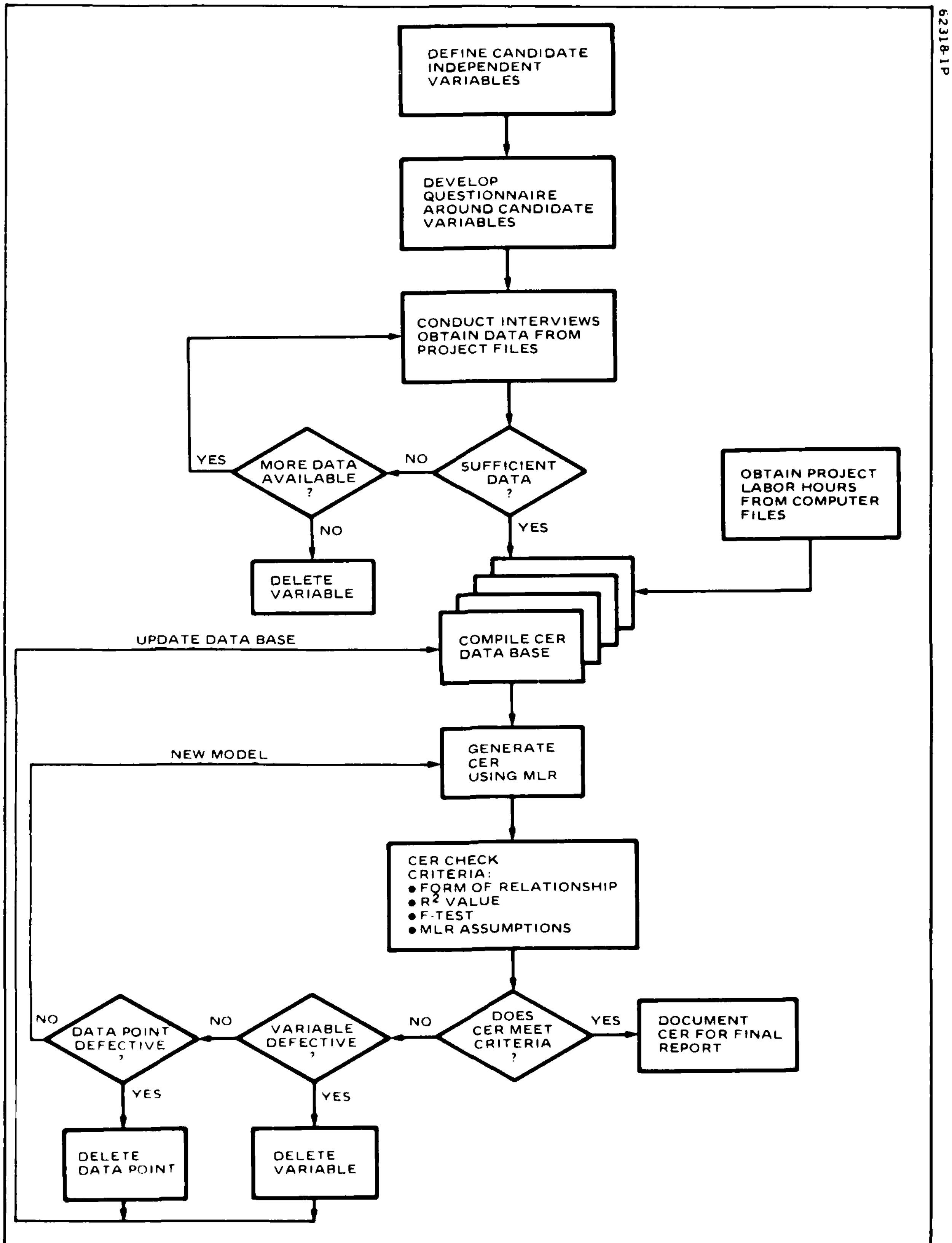

Figure 2.2-1. Data Processing Flow Diagram

- R^2 value/F-Test - The variable either did not have correlation with cost or was highly correlated with another (better) variable.

- MLR assumptions - The dependent or independent variable has correlation with the residual error (i.e., violates the assumptions of normality).

- Outliers - The data point is not typical of the rest of the data base. This type of defect was carefully examined to determine possible cause (e.g., a unique program characteristic which could be isolated from the data) and only removed if it could not be explained or was determined to be an uncorrectable error in data recording.

2.3 Program Characteristics Impacting R/M Task Costs. Tables 2.3-1, -2 and -3 provide a compilation of the variables which were found to have predictive value in estimating R&M task labor. The tables partition the variables as to whether they are program related (i.e., require general information on the test schedule and implementation of the R&M program), system related (i.e., require data on the number and complexity of the system), or task application related. The definition and range of values of each variable are provided in the paragraphs referenced in the tables. In addition, the R/M tasks that each variable is applicable to are noted in the last column of these tables.

TABLE 2.3-1. R&M PROGRAM RELATED VARIABLES

Description	Symbol	Definition	Applicable R/M Tasks
Number of R/M Tasks	NOT	3.1.1	101R/M
Reporting Formality	RF	3.1.1, 3.2.1, 3.4.1	101R/M, 203R/M
Duration of Implementation (FRACAS)	DOI	3.2.1	104R/M, 105R
Average Number of Units in FRACAS Program	ANU	3.2.1	104R/M, 105R
Number of Environmental Screens	NOS	3.6.1	301R, 303R, 304R
Requirements Complexity	RC	3.3.1	201R/M, 202R/M
Reliability Qualification Testing	RQT	3.6.1	301R, 303R, 304R
Production Reliability Acceptance Testing	PRAT	3.6.1	301R, 303R, 304R

TABLE 2.3-2. SYSTEM RELATED VARIABLES

Description	Symbol	Definition	Applicable R/M Tasks
Hardware Complexity	HC	3.2.1	104R/M, 105R, 201R/M, 202R/M, 203R/M, 204R/M, 301R, 303R, 304R
Modeling/Allocation Complexity	MAC	3.3.1	201R/M, 202R/M
Number of Unique Items	NOU	3.3.1, 3.5.1	201R/M, 202R/M, 204R/M
Repairable/Non-Repairable	RNR	3.3.1	203R/M
Percent of Commercial Equipment	POC	3.4.1	203R/M

TABLE 2.3-3. VARIABLES RELATED TO R/M TASK APPLICATION

Description	Symbol	Definition	Applicable R/M Tasks
Depth of Coverage	DOC	3.1.1	101R/M
Level of Detail (Analysis)	LOD	3.4.1, 3.5.1	203R/M, 204R/M

3.0 DETAILED DESCRIPTIONS OF R&M COST MODELS

3.1 R&M Program Plan (Task 101). The effort required to develop a program plan depends on the number of tasks included in the plan, the depth of coverage, and whether the plan requires formal customer approval or not.

Since the majority of R and M tasks are interrelated with overlapping "plan" coverage in most cases, it is usually not practical to plan-out the R-program separately from the M-program. This perception was reflected in the labor accounting records, where the split in labor charges between the R-program plan and M-program plan developments appeared to be arbitrary. Accordingly, when the labor charges were kept separate, very little correlation with the above factors was evident but when the labor charges were combined, a very high correlation was achieved (see Table 3.1.2-1). The validity of combining the labor charges was also justified in discussions with the Lead Engineers responsible for the R&M activities on many of the programs in the data base. These Lead Engineers were typically responsible for the R&M activities on many of the programs in the data base. Lead Engineers were also typically responsible for writing the R and M program plans (usually a single integrated plan) with inputs from assigned personnel.

3.1.1 Input Data Requirements. Table 3.1-1 gives the key program factors (independent variables) determined to have significant correlation with the cost of developing an "integrated" R&M program plan and provides range of applicability for each factor.

The following paragraphs discuss the meaning and any qualifying constraints on their use in the CER models (3.1.2):

Depth of Coverage (DOC). This variable represents the average amount of detail that is provided for each R&M task required by the contract. A small amount of detail (DOC=1) includes only a descriptive paragraph with referenced military standards, associated schedule milestones and an organization structure showing the relationship between R&M and project management. A medium amount of detail (DOC=2) adds the related procedures for accomplishing the task, describes the interfaces (inputs/outputs) from and/or to other disciplines (design engineering, manufacturing, QA, logistics, etc.), and a large amount of detail (DOC=3) adds R&M design guides and checklists.

TABLE 3.1-1. PROGRAM FACTORS CORRELATED WITH R&M PROGRAM PLAN DEVELOPMENT

Factor	Range of Application		
	Minimum	Maximum	Units
Depth of Coverage (DOC)	1	3	Scale
Number of R&M Tasks (NOT)	4	22	-
Reporting Formality (RF)	1	2	Scale

Number of R&M Tasks (NOT). This variable represents the total number of R&M tasks as defined by MIL-STD's 785 and 470.

Reporting Formality (RF). R&M plans can either be formal (RF=1), requiring review and approval action from the customer, or informal (RF=2), requiring only an internal program management review. In either case, the R&M plan(s) represents a contract to perform the stated R&M tasks in the manner described and, therefore, should be carefully written. However, in a formal (CDRL submittal) plan, closer scrutiny of the contents is made by both internal management and the customer resulting in additional labor expended on subsequent revisions.

3.1.2 Models. The general model for estimating the labor to develop R&M program plans has the form:

$$(3.1.2\text{-}1) \qquad T_{101} = (DOC)^{C_1} (NOT)^{C_2} (RF)^{C_3}$$

where: T_{101} = total labor (hours)

DOC = depth of plan coverage (see 3.1.1)

NOT = total number of R&M tasks required by MIL-STD's 785 and 470

RF = report formality (see 3.1.1)

C_1, C_2, C_3 = model coefficients (see Table 3.1.2-1)

Equation (3.1.2-1) estimates the labor necessary to produce both the R and M program plans even though, for formally submitted plans, separate CDRL's may be required. In addition, many of the program plans in the data base contain a certain amount of "lift" from the plans of prior programs. This is normal practice for companies who do substantial business with military agencies. Unfortunately, the amount of lift used to produce a given plan was not a quantifiable factor which could be incorporated in the model. The general experience of the R&M engineers interviewed, however, was that a typical program plan consisted of from 40 to 60 percent lifted material. Therefore, a newly developed program plan with little or no lifted material could take substantially more effort then estimated by (3.1.2-1).

Table 3.1.2-1 provides three models for making estimates based on available data. For example, if a program requires a plan which: (1) consists of 10 R&M Tasks, (2) demands a maximum depth of coverage for each task, and (3) involves Government review and approval, then using equation No. 3 in Table 3.1.2-1 results in the following estimate:

$$T_{101} = (DOC)^{0.532} (NOT)^{1.710} (RF)^{1.336}$$

$$= (3)^{0.532} (10)^{1.710} (2)^{1.336}$$

$$= 232 \text{ hours}$$

TABLE 3.1.2-1. CER MODELS FOR R&M PROGRAM PLANS

Equation No.	Model Coefficients (C_i)			P(>F)	R^2
	DOC	NOT	RF		
1	-	2.036	-	0.0001	0.960
2	-	1.829	1.228	0.0001	0.967
3	0.532	1.710	1.336	0.0001	0.969

The last two columns in Table 3.1.2-1 provide a significance test and multiple correlation coefficient for each model. Significance tests with probabilities less than 0.05 and R^2 values of greater than 0.9 are considered good fits. As can be seen, all of the equations in the table are excellent fits. Appendix B provides the complete regression analysis results.

3.1.3 Cost Tables. Tables 3.1.3-1 and 3.1.3-2 provide a global interpretation of the CER using equation No. 3 of Table 3.1.2-1. The other equations in Table 3.1.2-1 would, of course, result in a different set of values for estimating task labor.

Table 3.1.3-1 represents a breakdown of informal plan development labor hours and Table 3.1.3-2 the same breakdown for plans requiring a CDRL submittal. The plan depth-of-coverage(DOC) is typically reflected in the total number of pages included in the plan which is based on the amount of system/program detail that will be available during the contract period. This detail normally (but not always) follows the type of program: Concept Development, Validation, Full-Scale Development (FSD) and Production. For the systems in the data base, these associations with DOC are given in Table 3.1.3-3. If the contract is for system validation, for example, the program plan would typically be of medium depth of coverage and would normally require from 51 to 100 pages for documentation depending on the number of R&M tasks included. Some caution should be exercised to ensure that the number of R&M tasks and the depth of coverage are consistent with the program phase (e.g., an FMECA analysis would probably not be included in a plan for the Concept Development Phase since the necessary design detail is not available).

3.2 FRACAS/FRB (Tasks 104 and 105). The amount of effort required for Failure Reporting and Corrective Action System (FRACAS) implementation and Failure Review Board (FRB) participation is dependent on the "size" of the system or equipment being developed (measured in terms of the number of active components) and the average number of units under test or in use over a specified period of time. Average part quality is also a probable FRACAS/FRB cost factor since the use of low quality parts would be expected to cause more failure actions resulting in increased reporting, reviews and corrective actions. However, the range of part quality in the data base was typically JAN for semiconductors and from Class B-2 to Class B for micro- circuits, and within this range part quality was not a significant factor. This fact should be considered when applying the FRACAS/FRB CER in 3.2.2.

TABLE 3.1.3-1. TASK 101 R AND M PROGRAM PLAN - INFORMAL REPORTING (HOURS)

Number of R/M Tasks	Depth of Coverage		
	Small	Med	Large
5	16.	23.	28.
10	51.	74.	92.
15	103.	148.	184.
20	168.	242.	301.

TABLE 3.1.3-2. TASK 101 R AND M PROGRAM PLAN - CDRL REQUIRED (HOURS)

Number of R/M Tasks	Depth of Coverage		
	Small	Med	Large
5	40.	57.	71.
10	129.	187.	232.
15	259.	374.	464.
20	423.	612.	759.

TABLE 3.1.3-3. DEPTH OF COVERAGE VERSUS PROGRAM PHASE

Program Phase	Depth of Coverage (DOC)	Range of Page Count
Concept Development	Small	0 - 50
Validation - FSD	Medium	51 - 100
FSD - Production	Large	> 100

The effort required for participation in FRB activities is inseparable from the effort required for failure reporting and the taking of appropriate corrective actions. As a matter of company policy at Hughes-Fullerton, all deliverable projects require FRACAS in which the FRB is chaired by the project Technical Director and co-chaired by the lead R&M and Quality Assurance engineers.

3.2.1 Input Data Requirements. Table 3.2-1 gives the independent variables having significant correlation with the FRACAS/FRB activities and their ranges of applicability. The following paragraphs discuss the meaning of these variables and any qualifying constraints on their use in the CER models (3.2.2).

TABLE 3.2-1. PROGRAM FACTORS CORRELATED WITH FRACAS/FRB ACTIVITIES

Factor	Range of Application		
	Minimum	Maximum	Units
Duration of Implementation (DOI)	2.5	38.0	Months
Hardware Complexity (HC)	1	3	Scale
Average Number of Units On Test Per Month (ANU)	0.3*	30.0	-

* Only part of the system was tested.

Duration of Implementation (DOI). DOI represents the total calendar time expressed in months during which FRACAS is active. For the systems in the data base, this process generally started with integration and checkout of the first configuration item (CI) and continued until turnover of the final system to the customer.

Hardware Complexity (HC). HC is measured in terms of the number of electronic parts. (i.e., hybrids, integrated circuits semi-conductors resistors and capacitors.) The count should include all active redundant units and exclude "cold" standby units that are part of the system but are not under power until needed (i.e., switched in). The variable HC is scaled according to the following table:

TABLE 3.2-2. HARDWARE COMPLEXITY (HC) SCALING

System Class	Typical Range in Part Count	Scale
Equipment or Small System	< 15,000	1
Large Equipment or Medium Sized Equipment	15,000 - 25,000	2
Large System	> 25,000	3

Average Number of Units on Test Per Month (ANU). ANU is determined by an estimate of the average number of systems (i.e., "systems" represented by the value for HC) on which FRACAS data is being accumulated on a monthly basis.

3.2.2 Models. The general model for estimating the labor for implementing FRACAS/FRB has the following form:

$$(3.2.2\text{-}1)\quad T_{104/5} = (HC)^{C_1} (DOI)^{C_2} (ANU)^{C_3}$$

where:

$T_{104/5}$	=	total labor (hours)
HC	=	hardware complexity (see 3.2.1)
DOI	=	duration of FRACAS/FRB implementation (months)
ANU	=	average number of units (see 3.2.1)
C_1, C_2, C_3	=	model coefficients (see Table 3.2.2-1)

Equation (3.2.2-1) covers FRACAS/FRB activities occurring during all development phases of the program: manufacturing, equipment checkout and test, and during system integration, checkout and test (both in-plant and on-site). The labor involved in conducting detailed laboratory failure analyses (e.g., physics of failure) is not included in (3.2.2-1). This labor can run from 20 to 100 hours or more per analysis depending on the depth of analysis. In actual practice, the number of these analyses depends not only on the complexity of the system but also on the maturity of the design, development phase and the planned-versus-actual growth in R&M. Similarly, the time spent by the program Technical Director, Quality Assurance and the engineering design specialties in participating in FRB activities and in developing engineering design fixes is not included in (3.1.2-1). However, reliability growth monitoring and assessment (MIL-STD-785 Task 302) activities of the systems in the data base were logged under the FRACAS/FRB task and therefore included in (3.1.2-1).

Table 3.2.2-1 provides two models for estimating task labor based on available data. For example, if only the hardware complexity and the duration of FRACAS implementation are known (e.g., HC=2 and DOI=24 months) then reference to Table 3.2.2-1 results in the following estimate:

$$T_{104/5} = (HC)^{0.251} (DOI)^{2.496}$$

$$= (2)^{0.251} (24)^{2.496}$$

$$= 3316 \text{ hours } (= 138 \text{ hours/month})$$

TABLE 3.2.2-1. CER MODELS FOR FRACAS/FRB

Equation No.	Model Coefficients (C_i)			P(F)	R^2
	HC	DOI	ANU		
1	0.251	2.496	-	0.0001	0.994
2	0.810	2.279	0.221	0.0001	0.995

It should be noted that Equation No. 1 implicitly assumes an "average" number of units of complexity HC (i.e., the data base average for ANU) is in test for duration DOI. In this sense, the coefficients of the equation are adjusted to account for the absence of ANU.

The last two columns in Table 3.2.2-1 provide the model fit statistics. Both equations are considered excellent fits, with significance tests exhibiting probabilities well below 0.05 and R^2 values well in excess of 0.9. Appendix B provides the complete regression analysis results for these four equations.

3.2.3 <u>Cost Tables.</u> Equation No. 2 of Table 3.2.2-1 was used to generate Table 3.2.3-1. The variable representing hardware complexity (HC) defined above, can also be interpreted in terms of system MTBF. Table 3.2.3-2 categorizes HC by major equipment/system and associates part count with MTBF ranges.

TABLE 3.2.3-1. TASKS 104 AND 105 FRACAS/FRB (TOTAL HOURS)

Average Number of Units	Duration of Implementation								
	12 Months			24 Months			36 Months		
	Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System
1	288.	505.	701.	1397.	2449.	3401.	3520.	6170.	8568.
10	479.	840.	1167.	2326.	4077.	5661.	5859.	10270.	14262.
20	559.	979.	1360.	2711.	4572.	6600.	6830.	11973.	16626.
30	611.	1071.	1488.	2966.	5199.	7219.	7471.	13097.	18187.

TABLE 3.2.3-2. HARDWARE COMPLEXITY VERSUS MTBF

Category	Average Number of Electronic Parts	Range of MTBF (Hours)*
Equipment or Small System	7,500	2,500 - 13,000
Large Equipment or System	20,000	100 - 500
Large System	50,000	40 - 200

* Series Configurations

A medium sized system, for example, consisting of 20,000 electronic parts would be expected to have a range in series MTBF of between 100 and 500 hours. If an average of 10 systems are reported-on during a 24-month FRACAS period, Table 3.2.3-1 estimates the labor at 4077 hours. This labor does not include laboratory failure analysis, which can be added by using Table 3.2.3-2 and assuming a fraction of the expected number of failures will require analysis. This can be accomplished as follows:

$$T_{FA} = \text{(Expected failures/mo)(Fraction requiring failure analysis)}\ \text{(Labor hours/analysis)}$$

where: (Expected failures/mo) $= (\text{MTBF})^{-1}$(Operating hrs/mo/system)(10 systems)

$$= (300)^{-1}(720)(10) = 24^{(1)}$$

Therefore, in this example:

(Fraction requiring failure analysis) = $1.0^{(2)}$

(Labor hours/analysis) = 60 (using the mid-point in the range discussed in 3.2.2)

$$T_{FA} = (24)(1.0)(60) = 1440 \text{ hours/mo for failure analysis,}$$

and the total 24 month FRACAS/FRB effort is:

$$T_{104/5} = 4077 + (24)(1440) = 38{,}637 \text{ hours}$$

3.3 Modeling/Allocations (Tasks 201 and 202). The extent of activities involved in modeling a system architecture and the subsequent allocation of requirements, using this model, to a prescribed set of equipment and preliminary R&M prediction data are directly related to: (1) the number of successful operating modes, (2) the complexity of the R&M requirements, and (3) the number of equipment types. For the systems in the data base, standard series-paralleled configurations were modeled using generalized computer models. Therefore, modeling and allocation activities would be somewhat higher without these computer aids. For more complex models (see below), the development of unique analytical models or simulation programs were often required which resulted in a higher expenditure of labor. Similarly, repairable systems have an added degree of complexity because of the added requirements associated with maintainability which affects the allocation effort as well as the modeling activities.

3.3.1 Input Data Requirements. Table 3.3-1 gives the independent variables having significant correlation with the modeling and allocation activities and their ranges of applicability. The following paragraphs define the variables and identify any constraints on their use in the CER models (3.3.2):

Modeling/Allocation Complexity (MAC). MAC consists of three levels of complexity: (1) minimal complexity (MAC=1) representing a series configuration or a

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(1) Using the average MTBF for 20,000 parts.

(2) Assume, for example, that for every random failure (determined by MTBF) requires lab analysis.

TABLE 3.3-1. PROGRAM FACTORS CORRELATED WITH MODELING/ALLOCATION ACTIVITIES

Factor	Range of Application		
	Minimum	Maximum	Units
Modeling/Allocation Complexity (MAC)	1	3	Scale
Number of Unique Items (NOU)	7	445	-
Requirements Complexity (RC)	1	4	-

very small amount of redundancy; (2) medium complexity (MAC=2) involving a simple redundant system (i.e., a series-parallel network without interdependencies which can be represented by a general computer model); and (3) maximum complexity (MAC=3) involving any combination of nested structures, dependent subsystems, path sharing, etc. which require extensive model development effort.

Number of Unique Items (NOU). This variable applies to the number of unique items involved in the allocation process. For the systems in the data base, an "item" is generally defined as a procurable unit where the allocated R and/or M values become procurement specifications.

Requirements Complexity (RC). This variable pertains to the number of distinct models of the complexity specified by MAC for a complex system. For example, an air defense system may consist of several segments each of which has its own unique functional configuration and corresponding set of R/M requirements. RC acts as a significant multiplying factor to modeling and allocation complexity (MAC).

3.3.2 Models. The general model for estimating the labor requirements for system modeling and allocation activities has the following form:

(3.3.2-1) $T_{201/2} = (MAC)^{C_1} (NOU)^{C_2} (RC)^{C_3}$

where:

$T_{201/2}$ = total labor (hours)

MAC = modeling/allocation complexity (see 3.3.1)

NOU = number of unique items (see 3.3.1)

RC = requirements complexity (see 3.3.1)

C_1, C_2, C_3 = model coefficients (see Table 3.3.2-1)

System modeling activities consist of the development of reliability block diagrams and equations for estimating the various systems R&M and availability parameters. More complicated systems in the data base required more extensive requirements analysis and a top-level "functional FMEA" (i.e., to determine the effects of reconfiguration time, switching time, fault detection etc.) as a basis for developing the estimating equations (or simulation program). This "FMEA" effort is only for supporting the model development. Contractually required FMECA's are included under Task 204 (see 3.5). After the initial development, the models and equations are updated as the system design evolves into its final form, usually prior to the program critical design review (CDR).

R&M allocation activities involve use of the above models and inputs from the R&M predictions (Task 203 - see 3.4) to flow down the system requirements to designers, subcontractors and vendor product specifications. These activities include interfacing with and providing detailed R&M inputs (e.g., MTBF's, MTTR's, M_{Max}'s, fault detection and fault isolation criterion) to design and logistics analysis organizations.

Table 3.3.2-1 provides two models for estimating the combined activities of modeling and allocation. For a system composed of three complex subsystems (i.e., MAC=3 for each subsystem which has its own set of requirements) and consistency of 20 unique items (system total), Equation No. 2 gives the following labor estimate:

$$T201/2 = (MAC)^{2.031}(RC)^{2.071}(NOU)^{0.798}$$

$$= (3)^{2.031}(3)^{2.071}(20)^{0.798}$$

$$= 989 \text{ hours}$$

It should be emphasized in this example that the three subsystems are interpreted to be uniquely complex each requiring some model development.

TABLE 3.3.2-1. CER MODELS FOR MODELING AND ALLOCATIONS

Equation No.	Model Coefficients (C_i)			P(>F)	R^2
	MAC	RC	NOU		
1	4.350	-	0.866	0.0003	0.935
2	2.031	2.071	0.798	0.0011	0.950

The last two columns in Table 3.3.2-1 provide the model fit statistics. Both equations are considered excellent fits, with significance tests with probabilities well below 0.05 and R^2 values in excess of 0.9. Appendix B provides the complete regression analysis results for these equations.

3.3.3 Cost Tables. Table 3.3.3-1 represents a simplified form of equation No. 2 where RC is limited to four distinct modeling activities.

TABLE 3.3.3-1. TASKS 201 AND 202 MODELING/ALLOCATIONS (HOURS)

Unique Items	Distinct Models at MAC = 1				Distinct Models at MAC = 2				Distinct Models at MAC = 3			
	1	2	3	4	1	2	3	4	1	2	3	4
25.	13.	55.	127.	231.	53.	224.	519.	942.	122.	511.	1183.	2147.
50.	23.	95.	221.	401.	93.	390.	903.	1639.	211.	888.	2058.	3734.
200.	69.	289.	668.	1213.	281.	1179.	2731.	4956.	639.	2687.	6222.	11291.
300.	95.	399.	924.	1676.	388.	1630.	3775.	6849.	884.	3713.	8600.	15605.
400.	119.	502.	1162.	2109.	488.	2050.	4749.	8617.	1112.	4672.	10820.	19633.

3.4 R&M Predictions (Task 203). The amount of effort required to make R&M predictions depends on the complexity of the hardware and the level of detail at which the prediction is made. Systems in the data base for which detailed predictions were made utilized a computerized version of MIL-HDBK-217. Therefore, the effort involving tedious hand calculations for each component is replaced by the task of coding component characteristics for computer input.

3.4.1 Input Data Requirements. The following paragraphs define the independent variables having correlation with the prediction effort and Table 3.4-1 gives the application ranges:

Hardware Complexity (HC). This variable has the same meaning as in 3.2.1.

Level of Detail (LOD). LOD consist of three levels: (1) minimum level (LOD=1) in which the effort involves review of vendor furnished data; (2) medium level (LOD=2) requiring circuit card assembly, power supply, etc. estimates based on similar-to assessments and engineering analysis; and (3) maximum level (LOD=3) requiring a detailed piecepart prediction per MIL-HDBK-217 including appropriate thermal and electrical stress analyses.

Reporting Formality (RF). R&M prediction results can either be formally submitted (RF=2) resulting in added effort in subsequent technical clarifications and discussions with the customer, or they can be informal (RF=1) subject to only an internal management review. In the formal review, the added effort appears to be based on customer unfamiliarity with the prediction presentation format and/or concerns over the prediction ground rules and assumptions.

TABLE 3.4-1. PROGRAM FACTORS CORRELATED WITH R&M PREDICTION ACTIVITIES

Factor	Range of Application*		
	Minimum	Maximum	Units
Hardware Complexity (HC)	1	3	Scale
Level of Detail (LOD)	1	3	Scale
Reporting Formality (RF)	1	2	Scale
Percentage of Commercial (POC)	1	4	Scale
Repairable/Non-Repairable (RNR)	1	2	Scale

*Additional conditions on the application of these factors are required (see 3.4.2)

Percent of Commercial (POC). The R&M prediction activity is affected by the percentage of commercial (POC) hardware since the commercial hardware predictions (at the appropriate level of detail) are generally performed by the commercial manufacturer and only reviewed by the contractor. Although the manufacturer's effort in making R&M predictions is included in his bid to the contractor, this cost could not be broken-out and included in the CER models for the systems in the data base. The value of POC is scaled as follows:

Percentage of Commercial Hardware	Scale
0 - 25	4
26 - 50	3
51 - 75	2
76 - 100	1

Note that the highest value on the scale (POC=4) denotes the least amount of commercial hardware.

Repairable/Non-Repairable (RNR). This variable pertains to whether or not the system is repairable (RNR=2) while performing its basic mission with only temporary disruption of service. For example, ground based systems such as air defense systems are repairable, but fighter aircraft electronic systems are not repairable (RNR=1) while on a mission. Systems that are repairable in this sense generally require maintainability prediction effort.

3.4.2 Models. The general model for estimating the labor involved in making R&M predictions has the following form:

$$(3.4.2\text{-}1) \quad T_{203} = (HC)^{C_1}(LOD)^{C_2}(RF)^{C_3}(POC)^{C_4}(RNR)^{C_5}$$

where:

	T_{203}	= task labor (hours)
	HC	= hardware complexity (see 3.2.1)
	LOD	= level of detail (see 3.4.1)
	RF	= reporting formality (see 3.4.1)
	POC	= percent of commercial hardware (see 3.4.1)
	RNR	= repairable/non-repairable index (see 3.3.1)
	C_1, C_2, C_3, C_4, C_5	= model coefficients (see Table 3.4.2-1)

Equation (3.4.2-1) covers both R and M prediction effort starting with the earliest preliminary predictions and including all subsequent updates. For a minimal level of detail, this would involve, for example, reviewing and implementing changes (updates) to vendor-furnished data. For a maximum level of detail, the effort may start with similar-to estimates at this circuit card or unit level with updates eventually based on detailed MIL-HDBK-217 and/or MIL-HDBK-472 predictions as the design implementation details become known. Most of the systems in this data base required a combination of reviewing vendor R&M data and MIL-HDBK-217 predictions for newly developed equipment and/or interfaces. In these cases, an assessment was made based on interviews with the responsible R&M engineers as to where most of this labor was expended and a level of detail index was assigned accordingly.

When MIL-HDBK-217 predictions were required (i.e., for maximum level of detail), the systems in the data base generally included effort for the analysis of newly designed circuits to determine part operating stresses (electrical and thermal) as part of the prediction effort. Aside from the task-time analyses, MIL-HDBK-472 prediction efforts also included analyses of equipment fault isolation capability and the derivations of inputs for logistics support analyses (LSA's) such as MTTR's, M_{MAX}'s, fault isolation ambiguities etc.. These efforts are classified separately (Tasks 205 - maintainability analysis and 207 - preparation of LSA inputs) in MIL-STD-470, but were too integral to the prediction task effort to be broken out separately.

Table 3.4.2-1 provides four models for estimating R&M prediction task labor based on available data. The scales on the factors given in Table 3.4-1 cannot be used independently since the data base does not support extreme combinations (e.g., all factors taken at their minimum values). The following conditions apply to the models in Table 3.4.2-1:

Equation No. 1: $HC + LOD + RF \geq 4$

Equation No. 2: $HC + LOD + RF + POC \geq 8$

Equation No. 3: HC + LOD + POC + RNR $\geq$ 7

Equation No. 4: HC + LOD + RF + POC + RNR $\geq$ 9

If the input data does not satisfy the corresponding condition given above for a selected equation, the computed result will be invalid. For example, the effort required for a detailed R&M Prediction of a complex (i.e, HC = 3) repairable system consisting of 50 percent commercial equipment satisfies the condition for Equation No. 3 since:

$$HC + LOD + POC + RNR = 3 + 3 + 3 + 2 = 11 > 7$$

Therefore, the prediction labor is:

$$T_{203} = (HC)^{0.786}(LOD)^{2.103}(POC)^{1.643}(RNR)^{2.076}$$

$$= (3)^{0.786}(3)^{2.103}(3)^{1.643}(2)^{2.076}$$

$$= 613 \text{ hours}$$

TABLE 3.4.2-1. CER MODELS FOR R&M PREDICTIONS

Equation No.	Model Coefficients (Ci)					P(>F)	R^2
	HC	LOD	RF	POC	RNR		
1	1.125	3.285	5.164	-	-	0.0001	0.947
2	1.308	2.469	3.343	1.489	-	0.0001	0.963
3	0.786	2.103	-	1.643	2.076	0.0001	0.966
4	0.861	2.139	1.840	1.315	1.438	0.0001	0.971

The last two columns in Table 3.4.2-1 provide the model fit statistics. The equations in the table are all considered good fits, with significance tests exhibiting probabilities well below 0.05 and R^2 values in excess of 0.9. The complete regression analysis results for these equations are given in Appendix B.

3.4.3 Cost Tables. Equation No. 4 of Table 3.4.2-1 was used to generate cost Tables 3.4.3-1 and 3.4.3-2 for non-repairable and repairable equipment/systems. As in previous cost tabulations, hardware complexity (HC) is categorized into three groupings of equipment/systems (also see Table 3.2.3-2).

Using the above example, Table 3.4.3-2 would be used since the system is repairable. The level of the prediction is "detailed" (i.e., part level), the system is complex (i.e., a large system), and consists of 50 percent commercial equipment. The last column of Table 3.4.3-2 shows two cases: informal reporting (RF=0) resulting in 313 hours, and formal reporting (RF=1) resulting in 1122 hours.

TABLE 3.4.3-1. TASK 203 PREDICTIONS - NON REPAIRABLE (HOURS)

Percentage Commercial		Prediction Level of Detail								
		Equipment Item Analyzed			Assembly Item Analyzed			Part Item Analyzed		
		Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System
RF = 0	76-100	*	*	*	*	*	*	*	*	*
	51-75	*	*	*	*	*	*	*	*	68.
	26-50	*	*	*	*	*	49.	*	82.	116.
	0-25	*	*	16.	*	50.	71.	66.	120.	169.
RF = 1	76-100	*	*	*	*	*	*	*	*	97.
	51-75	*	*	*	*	*	102.	*	171.	242.
	26-50	*	*	40.	*	123.	174.	161.	292.	414.
	0-25	*	41.	58.	99.	180.	255.	236.	428.	606.

*The models do not apply for these conditions.

TABLE 3.4.3-2. TASK 203 PREDICTIONS - REPAIRABLE (HOURS)

	Percentage Commercial	Prediction Level of Detail								
		Equipment Item Analyzed			Assembly Item Analyzed			Part Item Analyzed		
		Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System	Equip/ Small System	Large Equip/ System	Large System
RF = 0	76-100	*	*	*	*	*	*	*	*	73.
	51-75	*	*	*	*	*	77.	*	129.	183.
	26-50	*	*	30.	*	93.	132.	122.	221.	313.
	0-25	*	31.	44.	75.	136.	193.	178.	324.	459.
RF = 1	76-100	*	*	*	*	*	110.	*	185.	262.
	51-75	*	*	63.	*	194.	275.	255.	462.	656.
	26-50	*	76.	107.	183.	333.	471.	436.	792.	1122.
	0-25	61.	111.	157.	268.	487.	690.	638.	1159.	1643.

*The models do not apply for these conditions.

3.5 FMECA (Task 204). The amount of effort required to conduct a failure mode, effects and criticality analysis depends on the number of items involved in the analysis, how complex the system is and depth of the analysis (or level of detail). All of the analyses for systems included in the data base were conducted in accordance with MIL-STD-1629.

3.5.1 Input Data Requirements. The following paragraphs define the independent variables having correlation with FMECA effort and Table 3.5-1 gives the application ranges:

Number of Unique Items (NOU). This variable requires an estimate of the total number items (as defined below) requiring an FMECA at the specified level of detail.

Level of Detail (LOD)	Type of Items Counted
Equipment Interface	Equipment
Equipment	Equipment
Circuit Card Assembly	Circuit Card
Piecepart	Circuit Card

For example, if two equipment items required an FMEA at the equipment level (i.e., considering the equipment as "black box"), and five newly designed cards (used in both equipment) required an FMEA at the piecepart level, then the value of NOU for the equipment level would be 2 and the value of NOU for the piecepart level would be 5. Each FMEA would be computed separately using a model defined in 3.5.2 and then combined to obtain the total FMEA effort estimate.

Hardware Complexity (HC) - This variable has the same meaning as in 3.2.1.

Level of Detail (LOD) - LOD consists of four levels: (LOD=1) equipment interface (i.e., the effects of each loss of function on the system is examined); (LOD=2) equipment; (LOD=3) circuit card assembly; and (LOD=4) piecepart.

TABLE 3.5-1. PROGRAM FACTORS CORRELATED WITH FMECA ACTIVITIES

Factor	Range of Application		
	Minimum	Maximum	Units
Number of Unique Items (NOU)	3	206	-
Hardware Complexity (HC)	1	3	Scale
Level of Detail (LOD)	1	4	Scale

3.5.2 Models. The general model for estimating the labor required to conduct an FMECA has the following form:

(3.5.2-1) $T_{204} = (NOU)^{C_1} (HC)^{C_2} (LOD)^{C_3}$

where:

T_{204} = task labor (hours)

NOU = number of units analyzed (see 3.5.1)

HC = hardware complexity (see 3.2.1)

LOD = level of detail (see 3.5.1)

C_1, C_2, C_3 = model coefficients (see Table 3.5.2-1)

Equation (3.5.2-1) estimates the labor for conducting a "manual" type of FMECA. The automated tools to assist in the analysis bookkeeping and report generation currently available (e.g., RADC-TR-84-244) did not exist for the systems in the data base. Automated tools can greatly reduce the labor for a piecepart FMECA and, to a lesser extent, a card-level FMECA (i.e., treating the circuit card as a black box). On an equipment-level or equipment interface level FMECA, however, the effect would be insignificant because of the significantly fewer failure modes to consider. Therefore, the FMECA labor estimated by equation (3.5.2-1) for the maximum level of detail will be biased on the high side whenever automated tools are employed. Unlike the R&M prediction task discussed previously, combined levels of FMECA's were not conducted for any of the systems in the data base. For complex systems, however, it is reasonable for an FMECA to be required on newly developed equipment and also on the total system (e.g., an equipment interface level FMECA). In this situation, equation (3.5.2-1) could be used to estimate these FMECA efforts separately (see below).

Table 3.5.2-1 provides three models for estimating FMECA task labor based on available data. Using equation No. 3, suppose that a detailed (i.e., piecepart) FMECA is to be conducted on five interface cards that are new design and on the entire system consisting of 15 major equipment (i.e., conducted at the equipment interfaces.) The total system is considered complex (i.e., HC = 3). The equation variables and FMECA estimates are given below:

a. Circuit Card FMECA:

$$T_{204} = (NOU)^{1.362} (HC)^{1.897} (LOD)^{1.315}$$

$$= (5)^{1.362} (3)^{1.897} (4)^{1.315}$$

$$= 445 \text{ hours}$$

b. System FMECA:

$$T_{204} = (15)^{1.362} (3)^{1.897} (1)^{1.315}$$

$$= 321 \text{ hours}$$

The total FMECA effort from a. and b. is 766 hours.

TABLE 3.5.2-1. CER MODELS FOR FMECA

Equation No.	Model Coefficients (Ci)			P(>F)	R^2
	NOU	HC	LOD		
1	1.899	-	-	0.0002	0.945
2	1.490	2.666	-	0.0004	0.981
3	1.362	1.897	1.315	0.0029	0.986

The last two columns in Table 3.5.2-1 provide the model fit statistics. The equations in the table are all considered good fits, with significance tests showing probabilities less than 0.003 and R^2 values greater than 0.94. The complete regression analysis results for these equations are given in Appendix B.

3.5.3 Cost Tables. Equation No. 3 of Table 3.5.2-1 was used to generate Table 3.5.3-1, approximations of the previous results using (3.5.2-1) can be read directly from the table entering the appropriate values for HC, NOU and LOD.

TABLE 3.5.3-1. TASK 204 FMECA/FMEA (HOURS)

Number of Unique Items (NOU)	Level of Detail (LOD)							
	Equipment Interface		Equipment		Circuit Card Assembly		Piecepart	
	Equip/ Small System	Large Equip/ System	Equip/ Small System	Large Equip/ System	Equip/ Small System	Large Equip/ System	Equip/ Small System	Large Equip/ System
5	9.	33.	22.	83.	38.	141.	55.	206.
25	80.	298.	199.	742.	340.	1265.	496.	1846.
50	206.	766.	512.	1906.	872.	3249.	1274.	4744.
100	528.	1968.	1315.	4898.	2242.	8349.	3273.	12190.
200	1358.	5057.	3379.	12586.	5760.	21454.	8410.	31322.

3.6 Reliability Testing (Tasks 301, 303 and 304). The amount of effort required to conduct reliability-type tests depends on hardware complexity, the number of pre-test environmental screens and the type of testing (i.e., whether testing is for qualification (RQT), production acceptance (PRAT) or both). The reliability effort involved for the systems in the data base did not include effort required to maintain the test facilities or the equipment under test. Therefore, the total effort required to conduct the test would be considerably higher than the values predicted by the CER's described in this section.

3.6.1 Data Input Requirements. The following paragraphs define the independent variables having correlation with the reliability testing activities. Table 3.6-1 gives the application ranges:

Hardware Complexity (HC). This variable has the same meaning as in 3.2.1.

Reliability Qualification Testing (RQT). RQT is an indicator variable which determines whether or not reliability qualification testing is conducted (RQT=1 denotes that the test is conducted, RQT=0 denotes that the test is not conducted).

Production Reliability Acceptance Testing (PRAT). PRAT is an indicator variable which determines whether or not production reliability acceptance testing is conducted (PRAT-1 denotes that the test is conducted, PRAT=0 denotes that the test is not conducted).

Number of Screens (NOS). NOS represents the number of environmental stress screens (ESS) that are conducted prior to the reliability demonstration test. Individual screens (e.g., temperature cycling, burn-in etc.) at each level of manufacture (circuit card, unit equipment and/or system) should be enumerated.

TABLE 3.6-1. PROGRAM FACTORS CORRELATED WITH R-TEST ACTIVITIES

Factor	Range of Application		
	Minimum	Maximum	Units
Hardware Complexity (HC)	1	3	Scale
Reliability Qualification Testing (RQT)	0	1	Indicator
Production Reliability Acceptance Testing (PRAT)	0	1	Indicator
Number of Screens (NOS)	0	28	-

3.6.2 Models. The general model for estimating reliability testing labor has the following general form:

$$(3.6.2\text{-}1)\quad T_{301/3/4} = C_1(HC) + C_2(RQT) + C_3(PRAT) + C_4(NOS)$$

where:

$T_{301/3/4}$ = task labor (hours)

HC = hardware complexity (see 3.2.1)

NOS = number of pre-test screens (see 3.6.1)

RQT = indicator for reliability qualification testing (see 3.6.1)

PRAT = indicator for production reliability acceptance testing (see 3.6.1)

C_1, C_2, C_3, C_4 = model coefficients (see Table 3.6.2-1)

Equation (3.6.2-1) estimates the reliability engineering effort for reliability-type testing, whether the test is qualification (RQT) or production reliability acceptance (PRAT), with appropriate pre-test screens (i.e., environmental stress screening (ESS)). Labor accounting for reliability development/growth was considered part of FRACAS (see 3.2) for the system in this data base. The effort includes the development of test plans and procedures, monitoring and recording the test activity failure classification and resolution of hardware failures and the formal documentation of the test results. In this sense, the reliability engineering effort is related to the failure activity rather than the test length. During ESS, the activity is much the same as the FRACAS effort, depending on the number of tests and the hardware complexity. Equation (3.6.2-1) does not include the test engineering effort to install the equipment/system in the test environment, develop and initiate the input stimuli and generally maintain the equipment and test facility. The effort required to maintain the system and test facilities, however, does relate to the length of the test, and can typically range from 2 to 4 or 5 manmonths per month of additional effort depending on the system complexity.

Table 3.6.2-1 provides four models for estimating the reliability engineering portion of the test effort.

TABLE 3.6.2-1. CER MODELS FOR R-TESTING

Equation No.	Model Coefficients (C_i)				P(>F)	R^2
	HC	RQT	PRAT	NOS		
1	285.1	-	-	-	0.0003	0.905
2	-	444.1	268.2	-	0.0014	0.928
3	-	418.7	239.4	3.1	0.0086	0.931
4	126.9	253.8	173.0	-	0.0040	0.954

Although data from the missing variables of the above equations (e.g., RQT, PRAT and NOS are missing from Equation No. 1) was not used in the regression, it should be noted (as in previous cases) that the remaining variables are constrained by the data base averages. For example, suppose the test system will go through 5 temperature cycling screens (e.g., 4 unit level and 1 system level) an RQT and a PRAT. Equation No. 3 provides the following estimate of the reliability engineering effort:

$$T_{301/3/4} = 418.7(RQT) + 239.4(PRAT) + 3.1(NOS)$$

$$= 418.7(1) + 239.4(1) + 3.1(5) = 673.6 \text{ hours}$$

Equation No. 3 assumes a test system of average complexity (i.e., weighted according to the values in the data base). On the other hand, if the only information known is that the test system is of average complexity (i.e., HC=2) then Equation No. 1 can be used to estimate the effort assuming a nominal (i.e., the data base average) amount of reliability screening and testing:

$$T_{301/4} = 285.1(HC) = 285.1(2) = 570.2 \text{ hours}$$

The last two columns in Table 3.6.2-1 provide the model fit statistics. The equations in the table are considered good fits, with significance tests showing probabilities less than 0.004 and R^2 values greater than 0.90. The complete regression analysis results are given in Appendix B.

3.6.3 Cost Tables. Equation No. 3 of Table 3.6.2-1 was used to generate Table 3.6.3-1. Note that the first column represents the labor hours for reliability support of the screening tests only and the last column includes pre-screening effort as well as the reliability support for RQT and PRAT.

TABLE 3.6.3-1. TASKS 301, 303, 304 REL TESTING (HOURS)

No. of Screens	Screening Only	Screening and PRAT	Screening and RQT	Screening, RQT and PRAT
5	16.	255.	434.	674.
10	31.	271.	450.	689.
15	47.	286.	466.	705.
20	63.	302.	481.	721.

4.0 INVESTIGATION INTO THE FEASIBILITY OF DERIVING COST/BENEFIT RATIOS

4.1 Candidate Approaches. There are several possible approaches to determining R&M program tasks benefits. Each approach must assign values to relevant and measurable figures of merit such as MTBF, MTTR, BIT effectiveness, etc. The exact figure of merit to be used is dependent on the approach found feasible and the degree to which information sources exist which support evaluation. Four approaches were investigated and one of these was selected to develop a preliminary model.

Ideally, the method of developing R&M Task Benefit-Indices is to make a quantitative assessment of the benefit prior to and after application of each individual task. The R&M task benefit would then be the gain in benefit experienced by applying the task. Aside from the availability of such data, this method is over simplified, and suffers from many inherent difficulties. For example, FMEAs can be done at various system and subsystem levels, so that the benefit gained from performing an FMEA is not just a function of whether or not the FMEA was applied, but also the level of application (i.e., "how much" FMEA is applied). Also, while many R&M tasks are only quantifiable as either being present or not, the benefit gained by applying such a task could depend on other factors as well, including equipment complexity, and the presence of other R&M tasks. A reliability modeling effort, for example, would make very little sense without the associated prediction effort which provides the input data used by the models. Thus, it is difficult to accurately assess the benefit gained from each task separately either quantitatively or subjectively. It is tacitly assumed in the approaches described below, therefore, that R&M tasks are to be grouped appropriately.

4.1.1 "Task-By-Task" Assessment Based on Hardware Engineering Changes. The reliability and maintainability impact of the hardware changes caused by the individual task, or composite set of tasks, is assessed to determine an appropriate change in the figure of merit associated with the task(s). This method is used for each task or group of tasks throughout the program until a point where the reliability and maintainability characteristics of the equipment have been reasonably established, usually at the conclusion of qualification testing.

The primary advantage of a task-by-task assessment of this type is that the approach is direct and traceable. The assessment of an improvement in equipment reliability or maintainability is dependent on evidence of a design change which was caused by the results of the task. The assessment of changes caused by a task requires that detailed engineering records be available throughout the development program. This level of detail is potentially realizable for a development program when hardware changes are formally documented in engineering change proposals (ECPs) and in test reports.

The main disadvantage found with a direct task-by-task assessment is that the amount of program data and level of detail required to use the method is prohibitive. Engineer notebooks, laboratory record books, and deliverable data items are normally available from the early equipment development period but these records do not contain sufficient detail to allow the large number of informal changes which occur as a result of R&M analyses to be identified or evaluated. Additionally, the direct task analysis approach, which necessarily relies on engineering judgment for assessment of changes due to R&M task performance (as opposed to other reasons) would be subjective and unique to Hughes. Therefore, a task-by-task assessment approach is not recommended as a basis for developing a benefits relationship.

4.1.2 Task Assessment by Case Study. Case studies which investigate the benefit of tasks in an R&M program tend to be subjective but are useful as general support for more quantitative analyses. The Institute for Defense Analysis (IDA) has conducted a number of these studies over the past several years. Although the R&M benefits for a given case are somewhat unique to the situation, an assessment across a number of programs should identify the major benefiting tasks. The following paragraphs summarize six IDA case studies which had applicable R&M information:

F-15 AN/APG 63 RADAR. This case study [3] also found that strong customer and program office management support are necessary for an effective R&M program. The study questioned the value of the "Laboratory" R Demo and found that "failure-free" burn-in/acceptance testing to be effective. Further, a field-FRACAS program was judged to be the most effective tool for identifying and correcting reliability problems.

F/A-18, AN/APG-65 RADAR. This study [4] did an item by item qualitative/quantitative analysis of the R&M Tasks performed during this program. The tasks which provided the "most return for the money" were TAAF, FRACAS, FRB and the worst case/stress analyses. The study was critical of the 100% piece part level FMECA as not effective. However, the study did find value in the FMECA as a tool at other levels.

F-16 AN/APG-66 RADAR. This case study [5] pointed out that strong management support from both the customer and program office are necessary for an effective R&M program. The "lessons learned" found that ESS at all levels of test to be very effective. As in the previous case, TAAF, FRACAS and FRB were again identified as effective.

T700 Jet Turbine Engine. The primary factor this study [6] pointed out was that reliability and maintainability must be "designed-in". The lessons learned dealt with quality factors more than purely R or M factors. However, vendor control was deemed to be very necessary.

AN/APN-128 Lightweight Doppler Navigation System. This case study [7] also stressed the need for management involvement for an R&M program to be successful. The R&M tasks found to be effective were the design analyses such as worst case, and thermal stress (hot and cold) analyses. ESS testing at all levels and FRACAS was also considered valuable.

4.0 INVESTIGATION INTO THE FEASIBILITY OF DERIVING COST/BENEFIT RATIOS

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FIREFINDER Weapons Locating Radar. The FIREFINDER case study [8] found the FRB, TAAF and R Growth tasks to be effective. However, FRACAS was seen as ineffective in the production phase of the program because of the lack of ability to effect change in the factory and because it tended to get mired in minutia which masked the "big swingers".

4.1.3 Task Assessment by Expert Opinion. The relative benefit obtained by the performance of various R&M program tasks can also be assessed through the use of expert opinion (e.g., as obtained from an industry survey.) The main advantage to this approach is that the assessment is simple to perform and provides an industry-wide input from the R&M community. Additionally, the expert opinion method may provide an industry concensus with the results of other approaches.

The disadvantages to this approach are that it is an entirely subjective, and usually non-qualitative approach, and there is also a risk of weak response to the survey. The expert opinion method of assigning R&M benefit changes to a specific task where quantitative data is weak, however, could be useful as a rough check on the reasonableness of the results of other, more objective methods.

4.1.4 Task Assessment by Linear Regression. The approach which showed the most promise in producing a quantitative result is through the use of linear regression analysis techniques. This approach has the advantage of being the most objective, requiring only an estimate of the total benefit (e.g., the observed MTBF) from each program and is consistent with the CER development. Additionally, the results of this method can be compared against the results of case studies and an industry expert opinion survey for consistency.

The only disadvantage associated with this approach is that the sample size must be sufficiently large to provide reasonable estimating accuracy.

5.0 CONCLUSIONS AND RECOMMENDATIONS

A method of estimating R&M task cost (i.e., labor hours) based on data that is normally available during the early program planning stages has been developed. The method consists of a set of six cost-estimating- relationships (CER's) which were derived from data on 23 projects using multiple linear regression (MLR) techniques. The CER's provide a tool for comparing alternate R&M program costs and guidelines for estimating what a specific R&M program should cost. Many of the MIL-STD 785 and 470 tasks required grouping in order to provide sufficient data to generate these CER's. A summarization of these groupings is provided in Table 1.2-1.

Several models are provided for each CER and those models consisting of the largest number of variables have the highest R^2 values and generally, provide more accurate estimates. Tabulations of each CER are also provided using the model with the highest R^2 value and should be applicable to most situations. The ranges of application of these models and tables (i.e., the ranges of values of the independent variables) and the identification of associated labor not accounted for in the estimates should be carefully noted in the detailed description of each CER (Section 3.0). The data base used to generate the CER's can be expanded by adding data points to the input data given in Appendix B (Tables B.6-1 through B.6-6) and adhering to the constraints on the variables given under the appropriate subsections of 3.0. The structure of the models developed should be sufficiently robust to be applicable in an expanded data base.

The benefits derived from implementing the various tasks in an R&M program are very difficult to measure directly except in special cases where the performance of a specific task (e.g., FMECA) led to the generation of identifiable cost-saving design changes. These before-and-after assessments are unique to each program and normally cannot be generalized.

For developing a usable benefits model in a follow-on study (i.e., one with a significantly wider application) a much larger sample size would be required. A sample size of 30 or more systems is recommended. In addition, industry questionnaires and case studies (both existing and new) should be included as supporting data for the model development in a follow-on study. Similarly, the long term (or life cycle) benefits of an R&M program such as the benefits derived in reduced spares, maintenance manpower and increased operational readiness should not be ignored. For example, a small gain in actual MTBF per system can have a substantial life cycle cost impact in these areas on a large deployment of such systems.

FIREFINDER Weapons Locating Radar. The FIREFINDER case study [8] found the FRB, TAAF and R Growth tasks to be effective. However, FRACAS was seen as ineffective in the production phase of the program because of the lack of ability to effect change in the factory and because it tended to get mired in minutia which masked the "big swingers".

4.1.3 Task Assessment by Expert Opinion. The relative benefit obtained by the performance of various R&M program tasks can also be assessed through the use of expert opinion (e.g., as obtained from an industry survey.) The main advantage to this approach is that the assessment is simple to perform and provides an industry-wide input from the R&M community. Additionally, the expert opinion method may provide an industry concensus with the results of other approaches.

The disadvantages to this approach are that it is an entirely subjective, and usually non-qualitative approach, and there is also a risk of weak response to the survey. The expert opinion method of assigning R&M benefit changes to a specific task where quantitative data is weak, however, could be useful as a rough check on the reasonableness of the results of other, more objective methods.

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APPENDIX A - APPROACH TO MODEL FITTING

Multiple linear regression (MLR) was used to analyze the data. This was deemed the most effective method for determining which aspects of a reliability program have significant effects on costs and for producing accurate cost estimating relationships (CER's). The basis assumptions of this technique are:

1. The dependent variable, Y (labor hours), is an intrinsically linear combination of p independent variables (hardware complexity, number of items, reporting formality). This relation is called the regression equation, and matrix notation the model is represented in the form

$$Y = X B + e$$

where

Y is an (n x 1) vector of the n observations of the dependent variable (labor hours)

X is an (n x p) matrix of observations of the independent variables

e is an (n x 1) vector of errors.

2. The elements e_i $1 \leq i \leq n$ of the vector e represent values of a normally distributed random variable. This assumption is reasonable since the error term is most probably the sum of errors from a large number of sources and, therefore, by the Central Limit Theorem, their sum will have a distribution that will be approximately normal, regardless of the type of probability distribution the separate error components may have.

3. The expected value of e is E (e) = (o) and the variance is V (e) = $I\sigma^2$, where I is the identity matrix, so the elements of e are uncorrelated. That is, E (Y) = XB.

The above imply that the error sum of squares is:

$$\begin{aligned} e'e &= (Y - XB)'(Y - XB) = Y'Y - B'X'Y - Y'XB + B'X'XB \\ &= Y'Y - 2Y'XB + B'XB \end{aligned}$$

The least squares estimate of B produces the least possible value of e'e. By differentiating with respect to B, setting the resulting equation to zero and replacing B by b, the so-called normal equation results

$$(X'X)b = X'Y$$

$$b = (X'X)^{-1}X'Y$$

This solution, b, called the least squares estimate of B, is the best linear, unbiased estimate. Further details are given in Draper and Smith.

Computer programs described below used this method to obtain estimates of B.

A.1 Intrinsically Linear Models. Models which are not linear but are "intrinsically linear" may be made linear (examples are illustrated in Figure A.1-1) by appropriate changes of variables. Two of the most common of these are the exponential model and the power function model.

An exponential model

$$Y = b_0 e^{b_1 X_1 + b_2 X_2}$$

can be made linear by taking natural logarithms of both sides to obtain:

$$\ln Y = \ln b_0 + b_1 X_1 + b_2 X_2$$

a power function model

$$Y = b_0 X_1^{b_1} X_2^{b_2}$$

can also be converted to a linear form by taking natural logarithms of both sides:

$$\ln Y = \ln b_0 + b_1 \ln X_1 + b_2 \ln X_2$$

Table A.1-1 contains the matrix forms after transformation of these nonlinear models to linear models.

TABLE A.1-1. EXAMPLE NON-LINEAR MODELS

Model Type	V Vector Form	X Matrix Form	B Vector Form
$X = b_0 e^{b_1 X_1 + b_2 X_2}$ (exponential)	$Y = \begin{pmatrix} \ln y_1 \\ \ln y_2 \\ \vdots \\ \ln y_n \end{pmatrix}$	$X = \begin{pmatrix} 1 & X_{11} & X_{12} \\ 1 & X_{21} & X_{22} \\ \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} \end{pmatrix}$	$B = \begin{pmatrix} \ln b_0 \\ b_1 \\ b_2 \end{pmatrix}$
$Y = b_0 X_1^{b_1} X_2^{b_2}$ (power function)	$Y = \begin{pmatrix} \ln y_1 \\ \ln y_2 \\ \vdots \\ \ln y_n \end{pmatrix}$	$X = \begin{pmatrix} 1 & \ln X_{11} & \ln X_{12} \\ 1 & \ln X_{21} & \ln X_{22} \\ \vdots & \vdots & \vdots \\ 1 & \ln X_{n1} & \ln X_{n2} \end{pmatrix}$	$B = \begin{pmatrix} \ln b_0 \\ b_1 \\ b_2 \end{pmatrix}$

These two nonlinear model are typical of the types of models that were fitted to the data.

A.2 Computer Methods. Multilinear regression analysis was performed using the Statistical Analysis System (SAS) multilinear regression computer procedures GLM and STEPWISE (see Appendix B). The initial search for acceptable CER's was performed with STEPWISE. As the name implies, the procedure examines a sequence of multiple linear equations in a STEPWISE manner. Potential predictors (i.e., independent variables) are added (forward regression) or deleted (backward regression) at each step. Thus, a sequence of regression functions

$$Y = b_0 + b_1 X_1$$

$$Y = b_0^1 + b_1^1 X_1 + b_2^1 X_2$$

$$\vdots$$

$$Y = B_0^{11} + b_1^{11} X_1 + \cdots + b_p^{11} X_p$$

is produced.

The predictors are not added arbitrarily. The program steers additions/deletions by statistical tests. The methods available within STEPWISE include MAXR, FORWARD AND BACKWARD. The STEPWISE MAXR procedure was used to develop the basic CERs for all tasks. The other procedures were used for checking and verifying the models obtained by use of MAXR. The SAS procedure GLM was used to obtain additional statistical information about the CERs that were otherwise acceptable.

MAXR or Maximum R^2 improvement is considered to be superior to FORWARD and BACKWARD described below and almost as good as all possible regressions. This method does not fix on a single model. Rather, it searches for the best one-variable model, the best two-variable model, etc. Initially, the one-variable model producing the highest R^2 is found. Of the remaining variables, the one that would give rise to the greatest increase in R^2 is included. The important aspect of this method is that it is not assumed to be the best two-variable model. Each variable in this two-variable model is compared to each variable not included in the model. All possible switches in variables are compared and the one producing the greatest increase in R^2 is made. The process continues until no switch could increase R^2. The two-variable model thus obtained is reported as the best two-variable model the technique can determine. The comparing-and-switching process is repeated for each additional variable. MAXR thus has the property that all variable switches are evaluated before any changes are made. This is an improvement over procedures in which the worst variable may be removed without consideration of the effect of adding the best remaining variable.

In FORWARD, the first step is, again, to find the one-variable model that shows the greatest R^2 value. For each of the remaining independent variables, F-statistics are computed. These reflect the variable's contribution to the model if it were included. The variable which has the largest F-value is added to the model (provided its significance level is above a certain predetermined threshold.) The process continues and variables are added one at a time until no remaining variable yields a significant F-statistic. Once a variable is added to the model, however, it is not removed.

In BACKWARD, statistics are calculated for a model including all the independent variables. These predictors are removed one by one until all remaining variables produce F-statistics above a given significance level.

A.3 Choice of Useful Models. The results in the last section described the computerized tools that were used to evaluate the various models. Generally, more than one potentially useful model was obtained for each R/M task. These models differ in the number of type of inputs required for their use. It is recommended that CERs exhibiting the best fit (i.e., highest R^2 value) be used whenever possible. But if it is not possible to get all the inputs for the best predictor, the remaining models should be selected in order of highest R^2 value.

In order to be considered effective, CER a model was required to explain at least 90% of the total variation of the regression (i.e., $R^2 = .90$) and be statistically significant at the 95% level.

A.4 Plausibility Checks. It is important to note that the final model selections (or CERs) do more than provide statistically significant predictors. At all stages of the process, candidates models were examined by reliability experts to ensure plausibility and usability. Checks were made to ensure that important program inputs known to relate to task cost were included. In addition, various sets of reasonable values of the independent variables were input using each CER to determine if the outputs were also reasonable. These efforts helped to ensure the usefulness of predictions made using the CERs.

APPENDIX B - REGRESSION ANALYSIS RESULTS

The following paragraphs define the statistics used in the analyses, the input data from the projects used, and provide the computer printouts of the results that were used to develop the R&M task cost-estimating-relationships (CERs)

B.1 R^2 Statistic. R is called the multiple correlation coefficient.

The objective of the linear least squares procedure is to account for as much of the total variability of the data as possible by means of the fitted equation.

Consider the following identity:

$$(B.1\text{-}1) \quad Y_i - \hat{Y}_i = (\bar{Y}_i - \hat{Y}) - Y_i - Y)$$

where

Y_i is observed labor hours at ith observation

$\hat{Y}_i$ indicates labor hours as estimated by the CER at ith set of conditions.

$\bar{Y}$ is the mean of the Y_i

Thus the residual $e_i = Y_i - \hat{Y}_i$ is the difference between:

a. The deviation of the observed Y_i from the overall mean, $\bar{Y}$, and

b. The deviation of the fitted $\hat{Y}_i$ from $\bar{Y}$, the mean of the observed values.

We can rewrite (B.1-1) as

$$(Y_i - \bar{Y}) = (\hat{Y}_i - \bar{Y}) + (\hat{Y}_i - Y).$$

If we square both sides and sum i = 1, 2, ... n, we obtain

$$(B.1\text{-}2) \quad \sum_{i=1}^{n} (Y_i - \bar{Y})^2 = \sum_{i=1}^{n} (\hat{Y} - \bar{Y})^2 + \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

(It is shown in Draper and Smith [2] that the cross-product term vanishes.)

The quantity $(Y - \bar{Y})$ is the deviation of the ith observation from the overall mean. So the left hand side of (B.1-2) is the sum of squares of deviations of the observations from the mean; shortened to SS about the mean. It is also called the corrected sum of squares of the Y's. As above Yi - Y is the deviation of the predicted, or fitted, value of the ith observation from the mean, and Y_1 - Y is the deviation of its observation from its predicted value (i.e., the ith residual), we can express (B.1-2) in words):

$$\begin{pmatrix}\text{Sum of Square}\\ \text{About the Mean}\end{pmatrix} = \begin{pmatrix}\text{Sum of Square}\\ \text{Due to Regression}\end{pmatrix} + \begin{pmatrix}\text{Sum of Squares}\\ \text{about Regression}\end{pmatrix}$$

This indicates that a way of determining the usefulness of the regression line as a predictor is to compare how much of the SS about the mean is in the SS due to regression and how much is in the SS about regression. We desire that the SS due to regression be much greater than the SS about regression, or that

$$R^2 = \frac{\text{SS due to regression}}{\text{SS about mean}}$$

be as close as possible to one.

B.2 Analysis of Variance Table. The above sums of squares, like any sum of squares, have associated degrees of freedom. This represents the number of independent pieces of information involving the n independent numbers Y_i, Y_2 ..., Y_n needed to compute the sum of squares. Consider $Y_i - \bar{Y}$, $Y_2 - \bar{Y}$, ..., $Y_n - \bar{Y}$. Only (n-1) are independent since all n of them sum to zero by definition of the mean. Thus, SS about the mean has (n-1) degrees of freedom.

The number of degrees of freedom for SS due to regression is equal to the number of coefficients determined by the fitting (not including the intercept). Each b_i, $i \geq 1$ is a function of $Y_1, Y_2, ..., Y_n$. Also

$$\sum (\hat{Y}_i - \bar{Y})^2 = \sum [b_0 + b_1 X_i + ... + b_p X_p) - (b_0 + b_1 \bar{X} ... b_p \bar{X}]^2$$

So there are only p independent pieces of information involving the Y_i needed to compute SS due to regression.

Now, by subtraction, the SS about regression has (n-1) - p degrees of freedom (df). The SS about regression is also called the residual sum of squares (since $Y_i - \hat{Y}_i$ are the residuals).

The computed error mean square is the statistic s^2, used as an estimate of the assumed fixed but unknown θ^2, variance of the error term of variance about regression. The variance about regression gives a measure of the error involved in predicting an observed value of Y from a given value of X using the determined model.

B.3 F-Test for Significance. The F-test was used to eliminate CER's that were not statistically significant. Consider the general CER defined by

$$y = b_0 + b_1 X_1 ... + b_p X_p + e.$$

This CER was eliminated from further study if the hypothesis

$$H_0 : b_i = 0 \qquad i = 1, 2, ..., p$$

(i.e., hypothesis that all coefficients should be zero) could not be rejected at the 95% level.

The test statistic is

$$F = \frac{\sum(\hat{Y}_i - \bar{Y})^2/p}{\sum(\hat{Y}_i - Y_i)^2/(n-p-1)} = \frac{\text{Mean Square Regression}}{\text{Mean Square Error}}$$

If $F > F_\alpha(p,n-p-1)$ for an F statistic with $\alpha = 0.05$ and the given degrees of freedom, H_0 was rejected and the CER was considered significant. On the computer printout (see B.6.1), Prob > F gives $1 - \alpha$ so if it was less than 0.05 the CER was taken as significant. If it was greater than 0.05 the CER was eliminated.

B.4 Analysis of Residuals. Recall that the residuals are defined as the n difference $e_i = Y_i - \hat{Y}_i$, $i = 1, 2, ..., n$. As before, Y_i is an observation and $\hat{Y}_i$ is the corresponding predicted value obtained by use of the fitted regression equation. Thus, the residuals, e_i, are the difference between what is observed and what the model predicted. We can also think of the e_i as the observed random errors if the model is correct. In performing regression analysis we have made the usual assumptions that the errors are independent, have zero mean, a constant (although unknown) variance, and follow a normal distribution. Tests were made to determine if the residuals conformed, or at least did not deny, these assumptions.

Draper and Smith [2] discuss plotting e_i vs $\hat{Y}$ to see if a normal distribution with mean zero and constant variance is reasonable. Figures B.4-1 through B.4-7 provide $e_i$vs. $\hat{Y}$ plots for each CER task and for the benefits relationship. Although some of the plots indicate a downward slope, the hypothesis of randomness could not be rejected. This conclusion is further supported by analyzing the sign runs (see B.5).

B.5 Analyzing Sign Runs in the Residuals. The pattern of signs (positive or negative) of the residuals was examined for each fit. For example, the pattern of signs of the residuals for R&M Program Plan (T_{101}) is

(+) (- -) (+) (-) (+ + + +) (- -) (+).

There are $n_1 = 7$ plus signs and $n_2 = 5$ minus signs. There are u = 7 "runs" as indicated by the parentheses. The probability of the occurrence of this arrangement if the residuals truly have mean zero is determined from [2] pages 160-161. The method for n_1, $n_2 > 10$ is given on page 159. The probability of 7 or fewer runs in the above arrangement is .413. Thus, on the basis of this test, we have no reason to reject the hypothesis of randomness with mean zero. The "runs" probability for each CER is given in Table B.5-1 and indicates that the assumption of randomness has not been violated.

B.6 Study Data Base. Tables B.6-1 through B.6-6 provide the data points used in generating the CER models. The corresponding computer outputs from the GLM and STEPWISE programs are given in B.7 and B.8

FIGURE B.4-1. TASK 101 R&M PROGRAM PLAN

PLOT OF RESID*YHAT   SYMBOL USED IS *

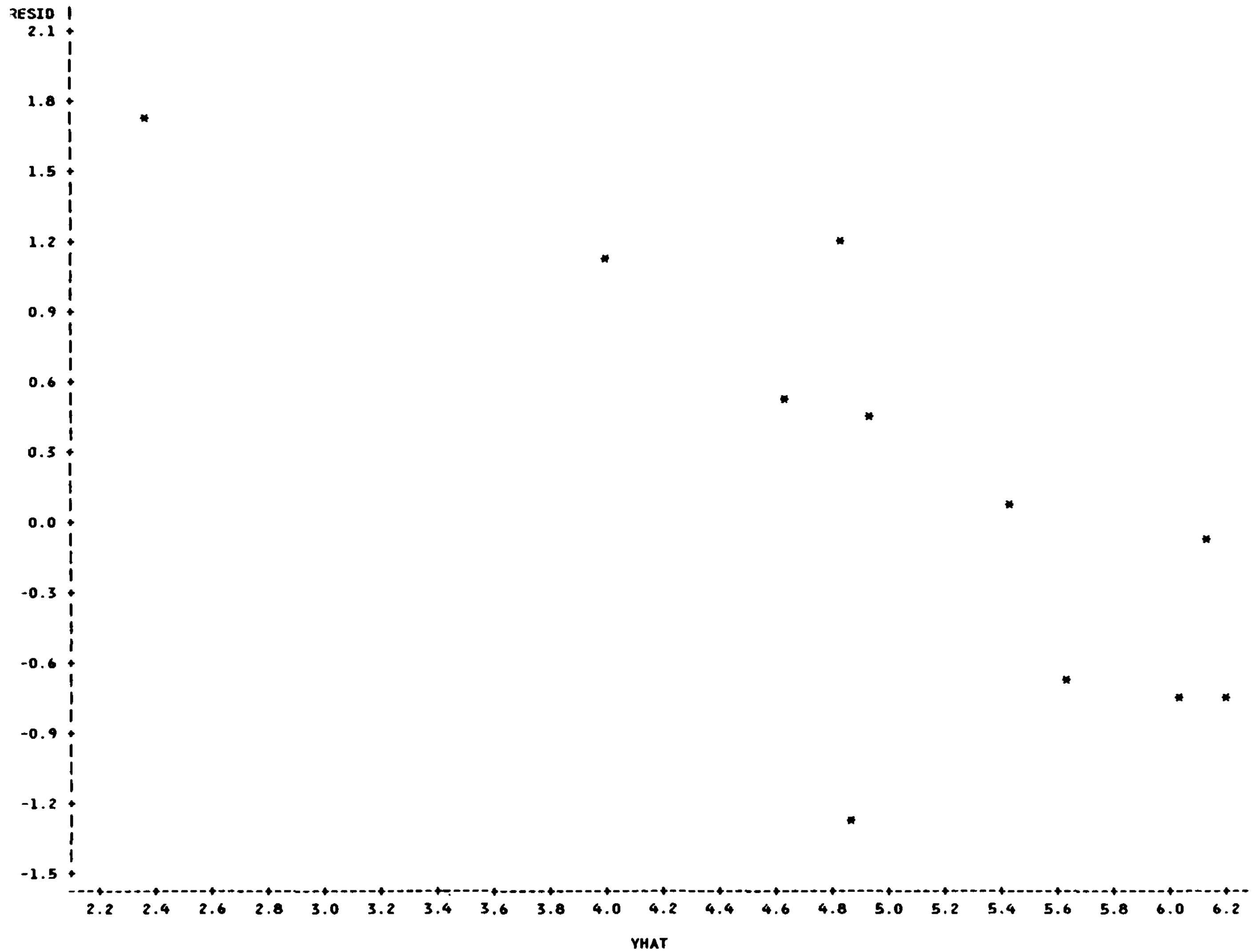

FIGURE B.4-2. TASKS 104 AND 105 FRACAS/FRB

PLOT OF RESID*YHAT   SYMBOL USED IS *

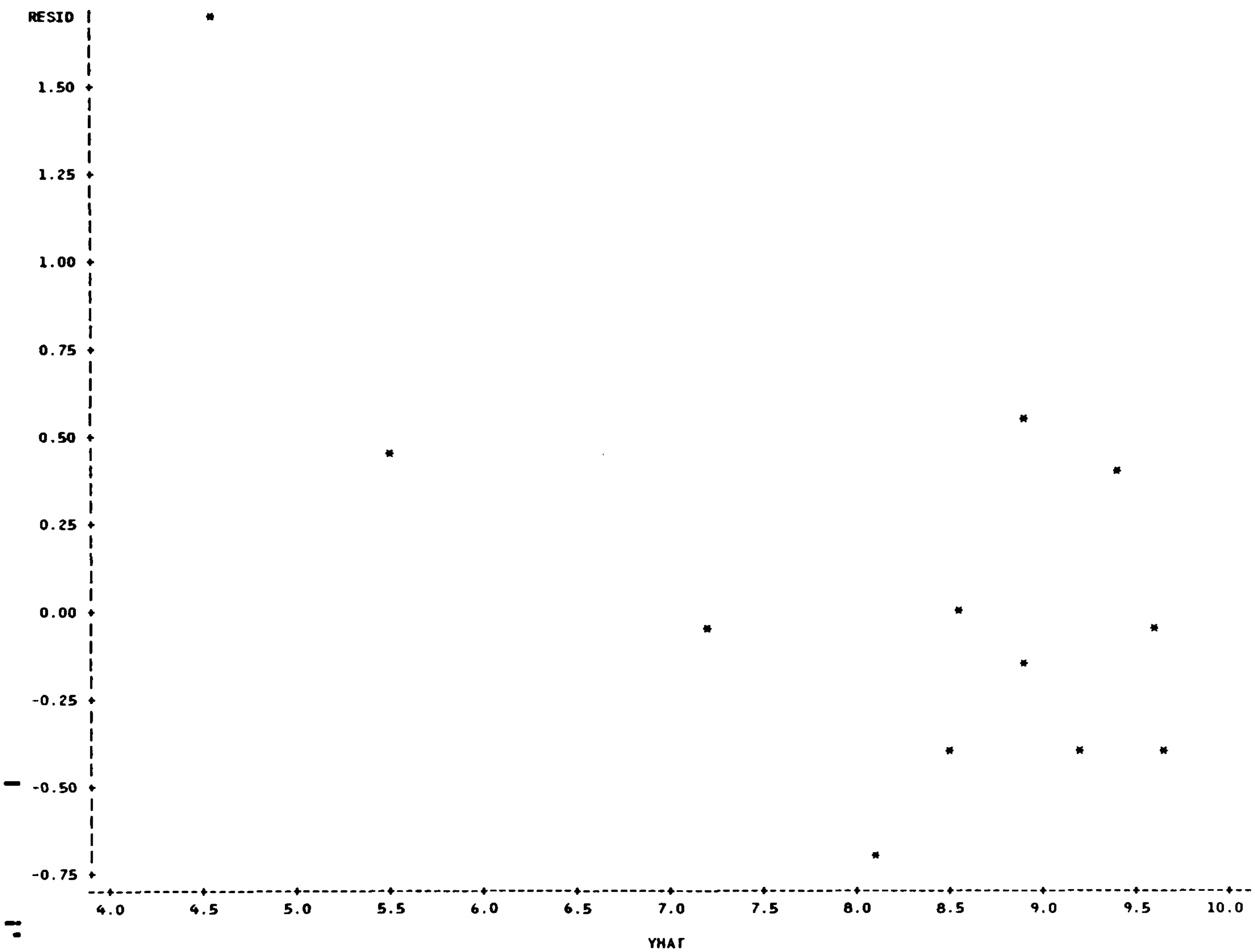

FIGURE B.4-3. TASKS 201 AND 202 MODELING ALLOCATIONS

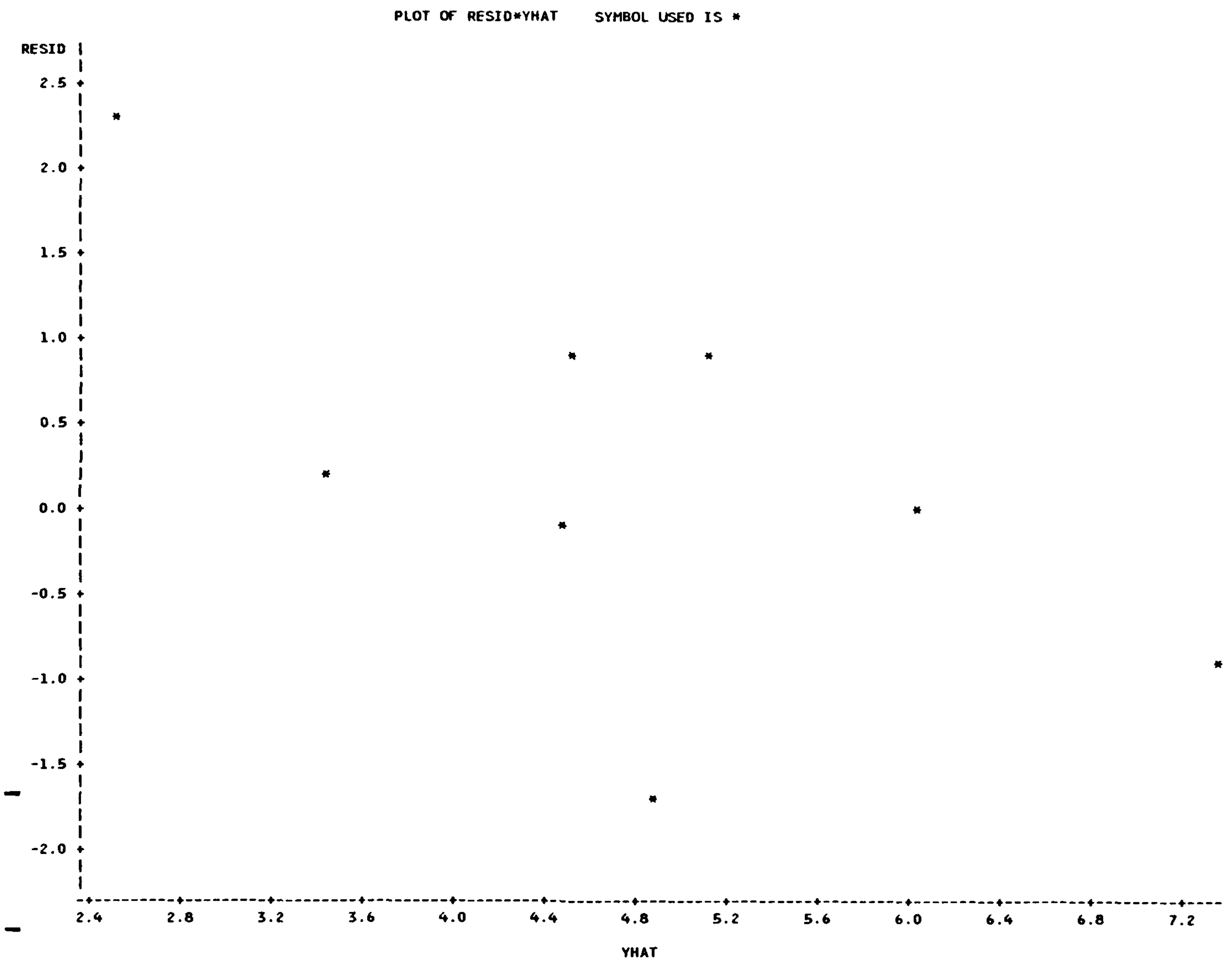

FIGURE B.4-4. TASK 203 PREDICTIONS

PLOT OF RESID*YHAT   SYMBOL USED IS *

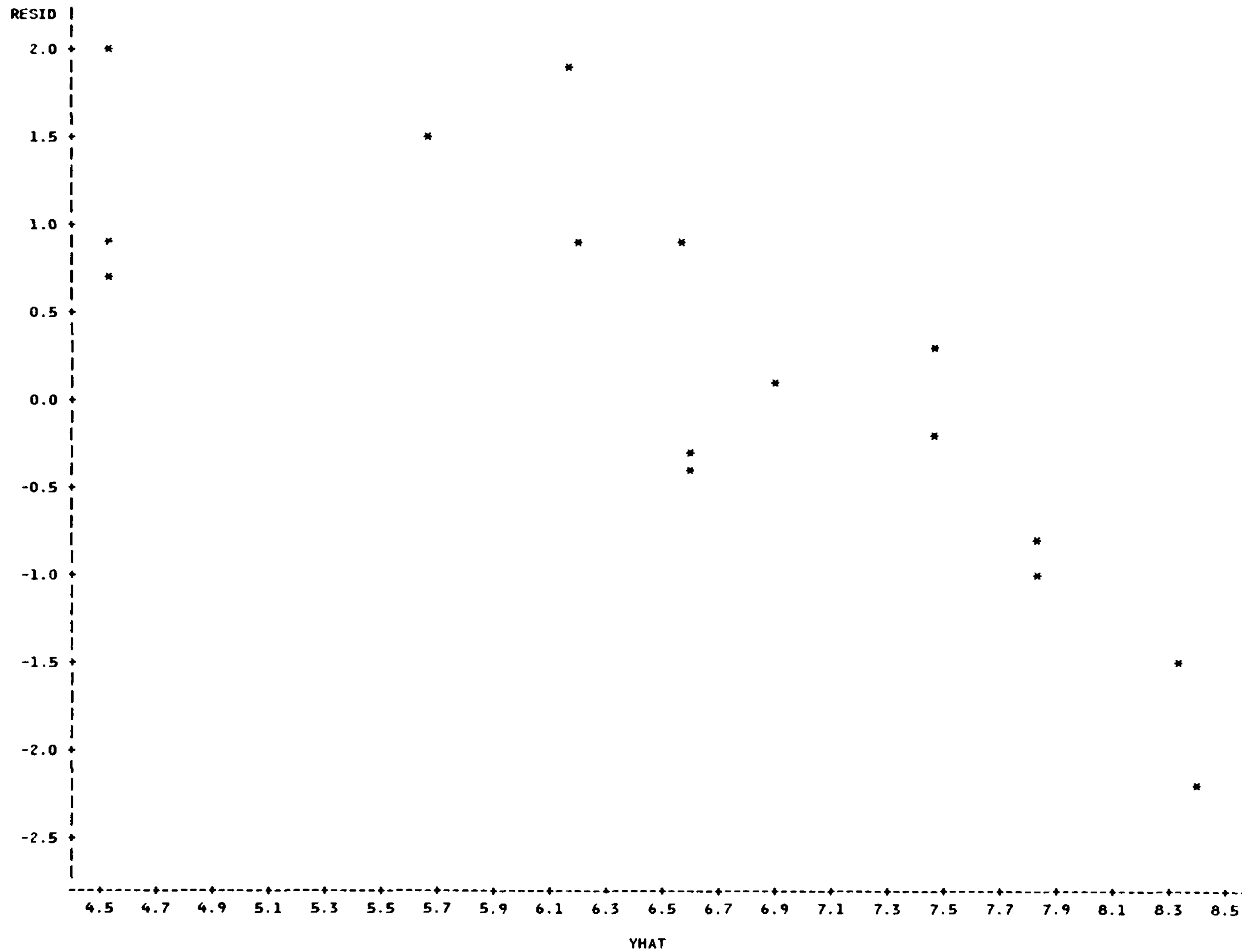

FIGURE B.4-5. TASK 204 FMECA/FMEA

PLOT OF RESID*YHAT SYMBOL USED IS *

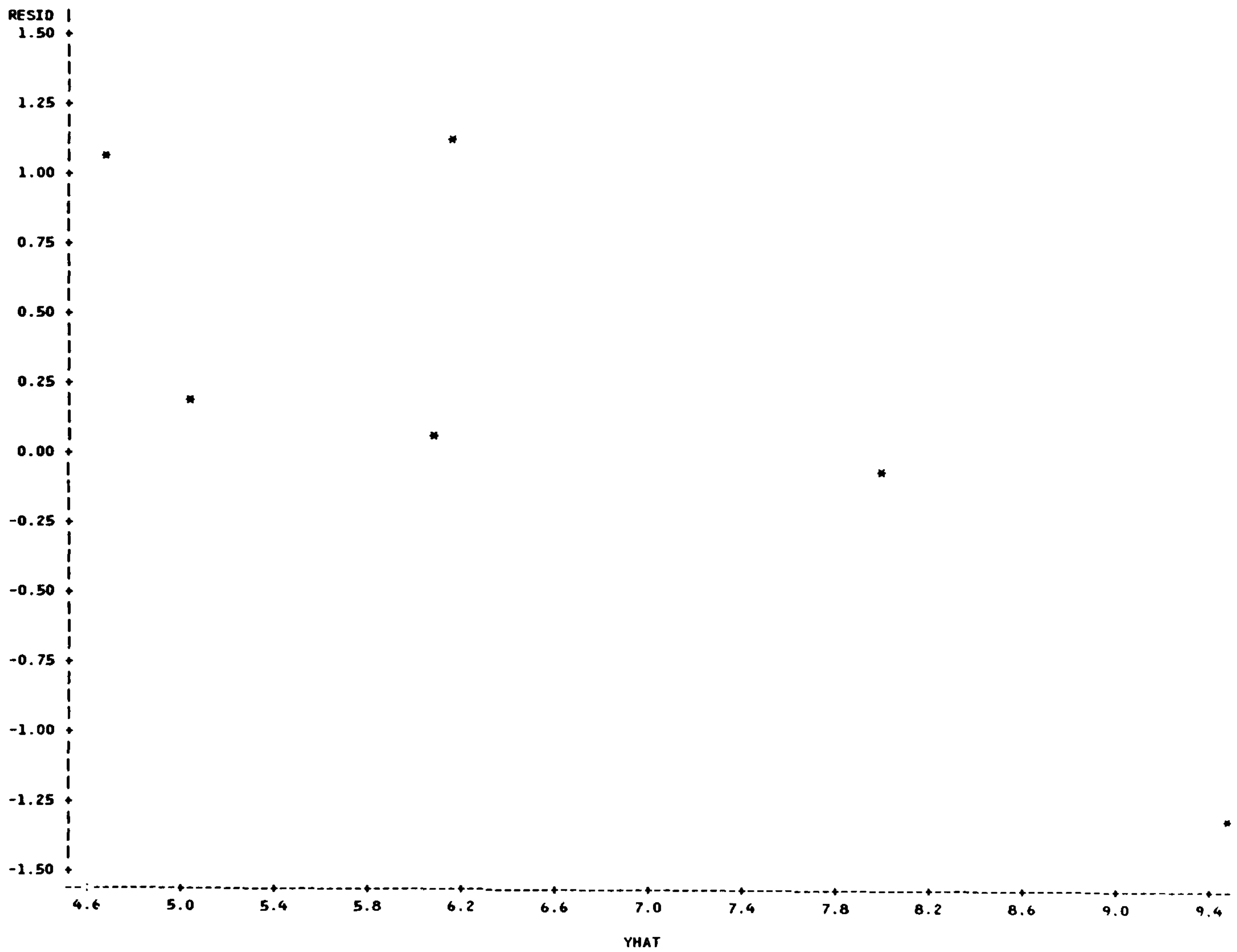

FIGURE B.4-6. TASKS 301 302 303 AND 304 REL TESTING

PLOT OF RESID*YHAT   SYMBOL USED IS *

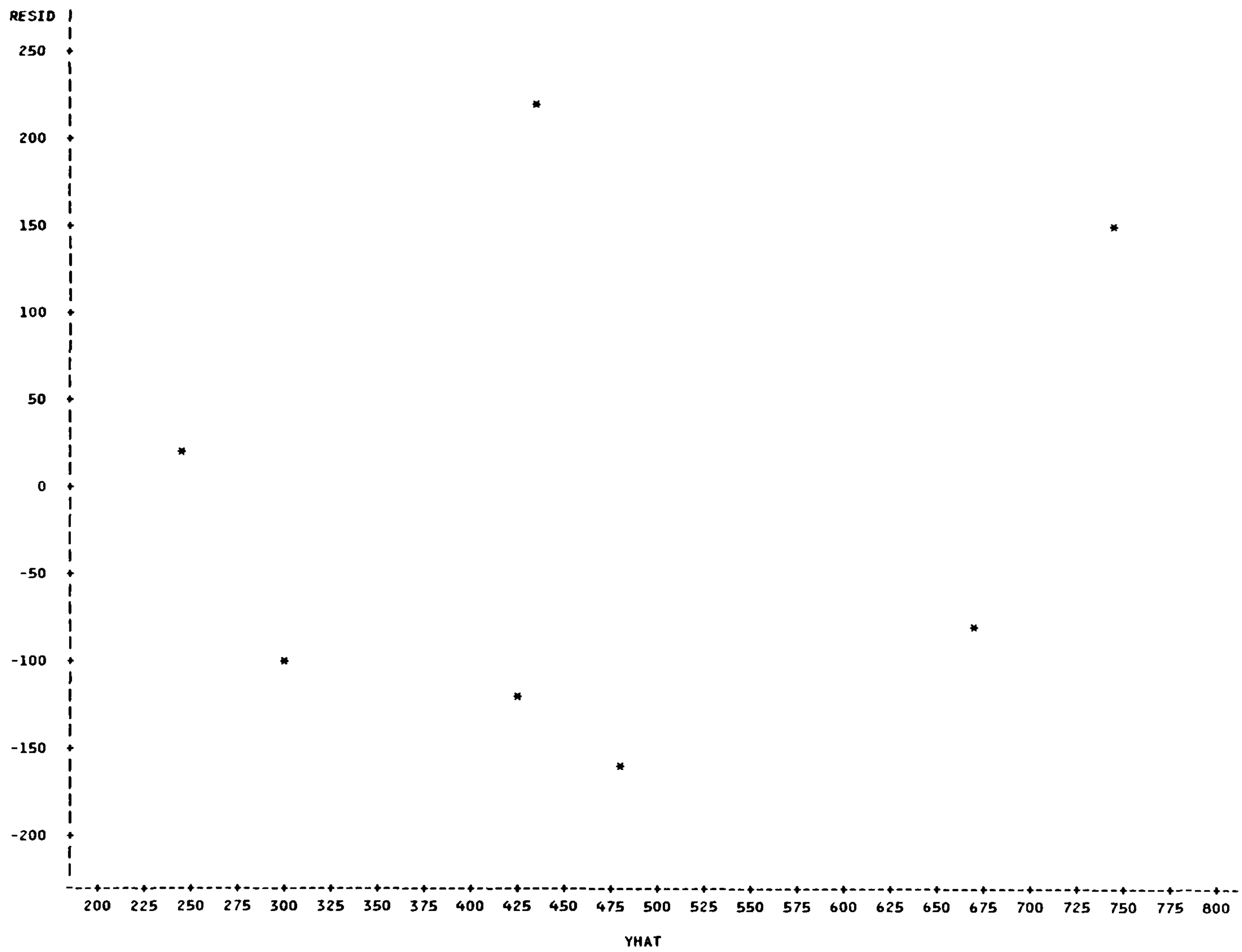

FIGURE B.4-7. ALL TASKS

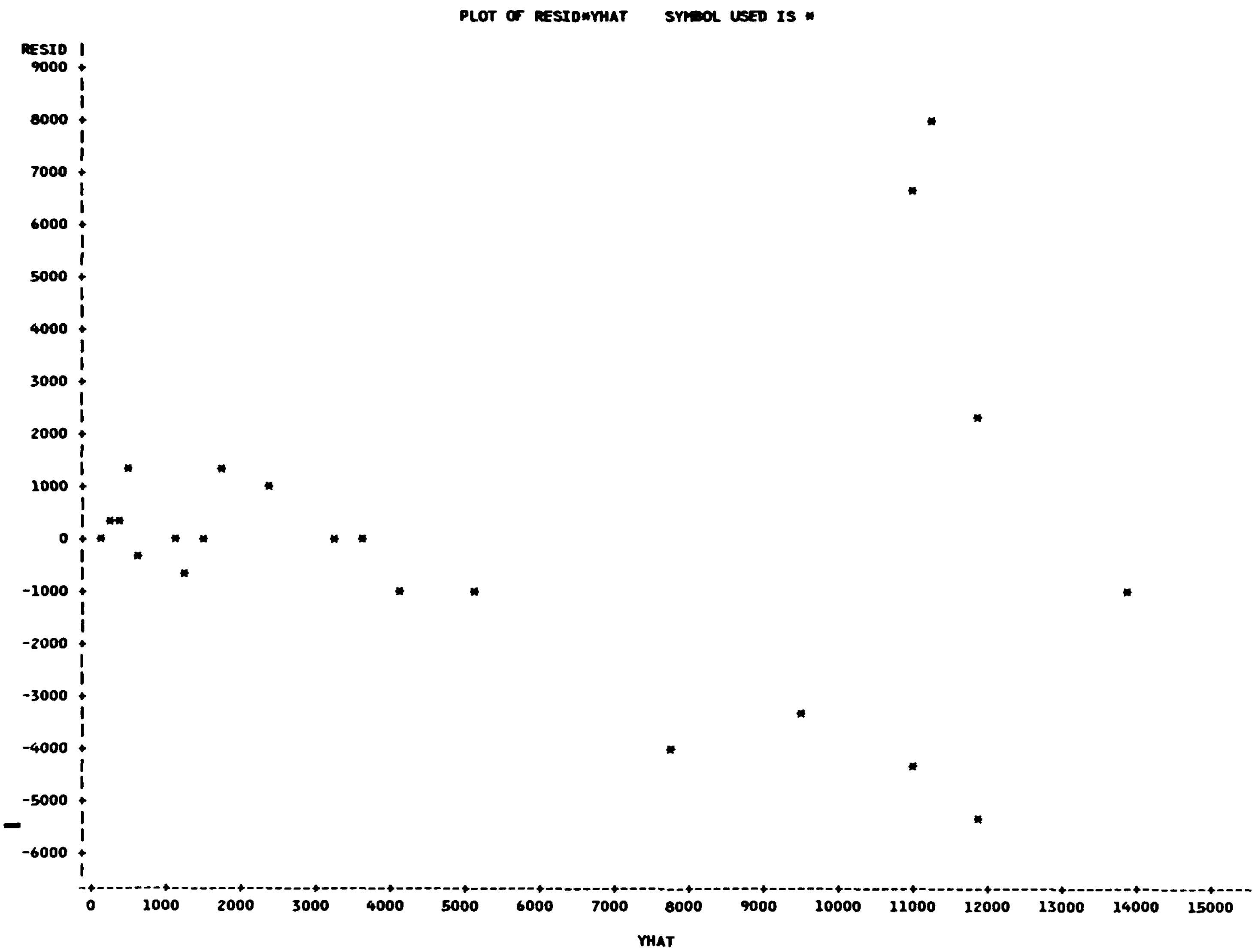

TABLE B.5-1. ANALYSIS OF SIGN RUNS IN THE RESIDUALS

CER	+ Signs (n_1)	- Signs (n_2)	Runs (u)	PROB ($\leq$ u)*
T_{101}	6	5	4	0.110
$T_{104/5}$	4	8	7	0.788
$T_{201/2}$	4	4	5	0.629
T_{203}	9	7	7	0.231
T_{204}	4	2	4	0.800
T301/3/4	3	4	6	0.971
$T_{R/M}$	10	12	11	0.425

* If PROB ($\leq$ u) is less than 0.05, randomness is rejected

TABLE B.6-1. INPUT DATA FOR T_{101}

Project No.	Actual Labor Hours	RF	NOT	DOC
212	35	2	10	1
312	168	2	7	2
324	218	1	18	1
325	240	1	17	3
335	61	1	4	1
340	204	2	16	2
522	145	1	19	3
518	436	2	17	2
327	241	2	22	1
420	428	2	8	2
122	162	2	6	1

TABLE B.6-2. INPUT DATA FOR $T_{104/5}$

Project No.	Actual Labor Hours	DOI (MOS)	ANU	HC
204	10523	36.21	15	3
212	5112	32.31	0.33*	3
214	12452	36.21	2	2
216	18018	36.21	20	2
312	3209	29.76	30	1
314	6216	35.98	2	2
335	532	5.77	1	2
403	14371	36.21	12	3
408	6586	38	1	3
518	1289	17.3	2	2
326	395	8.8	13	1
122	1672	23.76	1	3

*Partial System

TABLE B.6-3. INPUT DATA FOR $T_{201.2}$

Project No.	Actual Labor Hours	MAC	NOU	RC
204	24	1	445	1
216	40	1	75	1
403	123	1	24	1
522	650	2	47	4
520	80	1	273	1
518	416	2	17	2
327	218	1	47	2
122	415	3	7	3

TABLE B.6-4. INPUT DATA FOR T_{203}

Project No.	Actual Labor Hours	RF	HC	LOD	POC	RNR
204	1163	2	3	3	4	1
212	930	2	3	3	4	1
214	1519	2	2	3	4	1
216	1259	1	2	3	4	1
312	180	2	1	1	4	1
314	526	2	2	2	4	1
324	680	2	1	1	4	1
325	2327	2	2	3	4	1
335	1290	2	2	3	1	1
340	1069	2	1	3	4	1
403	3179	1	3	3	3	1
522	910	2	1	3	4	2
518	547	2	2	2	4	1
339	230	2	1	1	4	1
122	1810	2	3	2	1	2
508	480	2	3	2	4	[illegible]

TABLE B.6-5. INPUT DATA FOR T_{204}

Project No.	Actual Labor Hours	HC	NOU	LOD
204	Actual 178	3	3	3
522	1408	1	47	2
518	471	2	17	2
327	2782	2	47	3
420	315	2	12	1
415	3564	2	206	2

TABLE B.6-6. INPUT DATA FOR $T_{301/3/4}$

Project No.	Actual Labor Hours	NOS	RQT	PRAT	HC
204	900	28	1	1	3
214	300	2	1	0	2
312	269	2	0	1	1
324	318	20	1	0	1
325	654	6	1	0	2
340	207	20	0	1	1
520	585	3	1	1	1

B.7 Computer Output for GLM.

B.7.1 Explanation of Terms.* The GLM procedure [12] produces the following printed output by default:

a. The overall analysis-of-variance table breaks down the CORRECTED TOTAL sum of squares (1) for the dependent variable into the portion attributed to the MODEL (2) and the portion attributed to ERROR (3).

b. The MEAN SQUARE term is the SUM OF SQUARES divided by the DEGREES OF FREEDOM (DF) (4).

c. The MEAN SQUARE for ERROR, (MS(ERROR)), is an estimate of s^2, the variance of the true errors (7).

d. The F VALUE (8) is the ratio produced by dividing MS(MODEL) by MS(ERROR).

e. A small significance probability, PR>F, indicates that some linear function of the parameters is significantly different from zero. (9)

f. R-SQUARE, R^2, measures how much variation in the dependent variable can be accounted for by the model (10).

g. C.V., the coefficient of variation (11), which describes the amount of variation in the population is 100 times the standard deviation estimate of the dependent variable, ROOT MSE, divided by the MEAN. The coefficient of variation is often a preferred measure because it is unitless.

h. ROOT MSE (12) estimates the standard deviation of the dependent variable (or equivalently, the error term) and equals the square root of MS(ERROR).

i. MEAN (13) is the sample mean of the dependent variable.

j. The TYPE I SS (14) measures incremental sums of squares for the model as each variable is added.

k. The TYPE III SS (15) is the sum of squares that results when that variable is added last to the model.

l. This section of the output gives the ESTIMATES (16) for the model PARAMETERS-the intercept and the coefficients.

m. T FOR H0: PARAMETER = 0 (17) is the Student's t value for testing the null hypothesis that the parameter (if it is estimable) equals zero.

* The numbers in parentheses refer to the sample output.

n. The significance level, PR>|T|, (18) is the probability of getting a larger value of t if the parameter is truly equal to zero. A very small value for this probability leads to the conclusion that the independent variable contributes significantly to the model.

o. The STD ERROR OF ESTIMATE (19) is the standard error of the estimate of the true value of the parameter.

p. Observed values (20) of the dependent variable, Y.

q. Predicted values (21) of the dependent variable, $\hat{Y}$. Uses estimates from (16) in model.

r. Residual (22) or e_i, $\hat{Y}$ - Y.

s. 90% confidence intervals (23) (24) for $\hat{Y}$.

TABLE B.7.1-1. SAMPLE OUTPUT

TASK 101 R & M PROGRAM PLAN 11:43 TUESDAY, DECEMBER 3, 1985 2

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES (1)	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	288.17729184 (2)	96.05909728	82.50 (8)	0.0001 (9)	0.968687 (10)	20.9496 (11)
ERROR	8	9.31531090 (3)	1.16441386 (7)		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	11	297.49260274			1.07908010 (12)		5.15084839 (13)

SOURCE	DF	TYPE I SS (14)	F VALUE	PR > F	DF	TYPE III SS (15)	F VALUE	PR > F
DC	1	169.87501349	145.89	0.0001	1	0.51381131	0.44	0.5252
NT	1	115.89838652	99.53	0.0001	1	46.65666281	40.07	0.0002
RF	1	2.40389183	2.06	0.1887	1	2.40389183	2.06	0.1887

PARAMETER	ESTIMATE (16)	T FOR HO: PARAMETER=0 (17)	PR > |T| (18)	STD ERROR OF ESTIMATE (19)
DC	0.53200134	0.66	0.5252	0.80087471
NT	1.70968866	6.33	0.0002	0.27009334
RF	1.33563076	1.44	0.1887	0.92957114

OBSERVATION	OBSERVED VALUE (20)	PREDICTED VALUE (21)	RESIDUAL (22)	LOWER 90% CL INDIVIDUAL (23)	UPPER 90% CL INDIVIDUAL (24)
1	3.55534806	4.86249230	-1.30714424	2.64594888	7.07903572
2	5.12396398	4.62144443	0.50251955	2.38884348	6.85404538
3	5.38449506	4.94163580	0.44285926	2.46493938	7.41833223
4	5.48063892	5.42837592	0.05226300	3.05301951	7.80373234
5	4.11087386	2.37013174	1.74074212	0.24613607	4.49412741
6	5.31811999	6.03480741	-0.71668741	3.86155266	8.20806216
7	4.97673374	5.61853713	-0.64180339	3.23457556	8.00249870
8	6.07764224	6.13845663	-0.06081439	3.96649184	8.31042143
9	5.48479693	6.21050891	-0.72571197	3.89969989	8.52131792
10	6.05912320	4.84974154	1.20938166	2.63187690	7.06760617
11	5.08759634	3.98913953	1.09845681	1.79733761	6.18094145

SUM OF RESIDUALS	1.59406099
SUM OF SQUARED RESIDUALS	9.31531090
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	15.40444473
FIRST ORDER AUTOCORRELATION	-0.06160167
DURBIN-WATSON D	1.81025260

B.7.2 Output of GLM. Tables B.7.2-1 through B.7.2-7 provide the computer printouts for GLM.

TABLE B.7.2-1. TASK 101 R&M PROGRAM PLAN

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	288.17729184	96.05909728	82.50	0.0001	0.968687	20.9496
ERROR	8	9.31531090	1.16441386		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	11	297.49260274			1.07908010		5.15084839

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
DC	1	169.87501349	145.89	0.0001	1	0.51381131	0.44	0.5252
NT	1	115.89838652	99.53	0.0001	1	46.65666281	40.07	0.0002
RF	1	2.40389183	2.06	0.1887	1	2.40389183	2.06	0.1887

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
DC	0.53200134	0.66	0.5252	0.80087471
NT	1.70968866	6.33	0.0002	0.27009334
RF	1.33563076	1.44	0.1887	0.92957114

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	3.55534806	4.86249230	-1.30714424	2.64594888	7.07903572
2	5.12396398	4.62144443	0.50251955	2.38884348	6.85404538
3	5.38449506	4.94163580	0.44285926	2.46493938	7.41833223
4	5.48063892	5.42837592	0.05226300	3.05301951	7.80373234
5	4.11087386	2.37013174	1.74074212	0.24613607	4.49412741
6	5.31811999	6.03480741	-0.71668741	3.86155266	8.20806216
7	4.97673374	5.61853713	-0.64180339	3.23457556	8.00249870
8	6.07764224	6.13845663	-0.06081439	3.96649184	8.31042143
9	5.48479693	6.21050891	-0.72571197	3.89969989	8.52131792
10	6.05912320	4.84974154	1.20938166	2.63187690	7.06760617
11	5.08759634	3.98913953	1.09845681	1.79733761	6.18094145

SUM OF RESIDUALS	1.59406099
SUM OF SQUARED RESIDUALS	9.31531090
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	15.40444473
FIRST ORDER AUTOCORRELATION	-0.06160167
DURBIN-WATSON D	1.81025260

TABLE B.7.2-2. TASKS 104 AND 105 FRACAS/FRB

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	830.98867923	276.99622641	542.43	0.0001	0.994500	8.6582
ERROR	9	4.59595028	0.51066114		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	12	835.58462951			0.71460559		8.25355169

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
DOI	1	830.17427212	1625.69	0.0001	1	46.59135103	91.24	0.0001
HC	1	0.09049136	0.18	0.6837	1	0.58194929	1.14	0.3135
ANU	1	0.72391575	1.42	0.2643	1	0.72391575	1.42	0.2643

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
DOI	2.27880335	9.55	0.0001	0.23857262
HC	0.80975425	1.07	0.3135	0.75853753
ANU	0.22134263	1.19	0.2643	0.18590346

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	9.26131862	9.66840231	-0.40708369	8.11515110	11.22165351
2	8.53934600	8.56391192	-0.02456593	7.03746527	10.09035058
3	9.44963653	8.89409127	0.55554526	7.46140757	10.32677497
4	9.79912654	9.40375152	0.39537502	7.95839760	10.84910544
5	8.07371464	8.48518625	-0.41147161	6.86411831	10.10625419
6	8.73488189	8.87957052	-0.14468863	7.44783490	10.31130614
7	6.27664749	4.55527789	1.72136960	3.19423796	5.91630981
8	9.57296757	9.61901112	-0.04604356	8.09683963	11.14118362
9	8.79270146	9.17894951	-0.38624805	7.75044738	10.60745164
10	7.16162200	7.21090143	-0.04927943	5.85398012	8.56782275
11	5.97882576	5.52350416	0.45532160	4.07040661	6.97672171
12	7.42177579	8.10886296	-0.68708716	6.68920146	9.52852445

SUM OF RESIDUALS	0.95114344
SUM OF SQUARED RESIDUALS	4.59595028
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	6.74782311
FIRST ORDER AUTOCORRELATION	-0.11343699
DURBIN WATSON D	2.08809835

TABLE B.7.2-3. TASKS 201 AND 202 MODELING ALLOCATIONS

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	199.22950803	66.40983601	31.65	0.0011	0.949977	28.9835
ERROR	5	10.49089014	2.09817803		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	8	209.72039817			1.44850890		4.99769694

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
[illegible]	1	107.87490243	51.41	0.0008	1	1.82212973	0.87	0.3942
[illegible]	1	27.33247970	13.03	0.0154	1	3.12921975	1.49	0.2764
[illegible]	1	64.02212590	30.51	0.0027	1	64.02212590	30.51	0.0027

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
[illegible]	2.03085368	0.93	0.3942	2.17926556
[illegible]	2.07132059	1.22	0.2764	1.69610266
[illegible]	0.79822657	5.52	0.0027	0.14450481

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	3.17805383	4.86764490	-1.68959106	1.45125253	8.28403726
2	3.68887945	3.44633371	0.24254574	0.26838335	6.62428407
3	4.81218436	2.53680700	2.27537736	-0.52509839	5.59871238
4	6.47697236	7.35244175	-0.87546939	3.69794222	11.00694128
5	4.38202663	4.47762941	-0.09560277	1.13296952	7.82228930
6	6.03068526	5.10496224	0.92572302	1.81082538	8.39109909
7	5.38449506	4.50902567	0.87546939	0.85452614	8.16352521
8	6.02827852	6.05998503	-0.03170651	2.33628381	9.78368625

SUM OF RESIDUALS	1.62674577
SUM OF SQUARED RESIDUALS	10.49089014
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	[illegible].50998636
FIRST ORDER AUTOCORRELATION	-0.10218995
DURBIN WATSON D	1.93217009

TABLE B.7.2-4. TASK 203 PREDICTIONS

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	5	723.23955200	144.64791040	72.71	0.0001	0.970631	20.7950
ERROR	11	21.88325943	1.98938722		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	16	745.12281143			1.41045639		6.78265929

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
HC	1	521.94560808	262.37	0.0001	1	1.59822702	0.80	0.3893
LOD	1	114.68871052	57.65	0.0001	1	9.89075595	4.97	0.0475
RF	1	68.90420693	34.64	0.0001	1	3.22653075	1.62	0.2291
POC	1	11.75693907	5.91	0.0333	1	8.94029367	4.49	0.0576
RNR	1	5.94408740	2.99	0.1118	1	5.94408740	2.99	0.1118

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
HC	0.86071524	0.90	0.3893	0.96028450
LOD	2.13853624	2.23	0.0475	0.95909479
RF	1.83975538	1.27	0.2291	1.44461407
POC	1.31541501	2.12	0.0576	0.62050682
RNR	1.43787113	1.73	0.1118	0.83183470

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	7.05875815	7.83165933	-0.77290118	5.03468518	10.62863348
2	6.83518459	7.83165933	-0.99647474	5.03468518	10.62863348
3	7.32580750	7.48266933	-0.15686183	4.77138092	10.19395774
4	7.13807303	6.20744808	0.93062496	3.17594953	9.23894662
5	5.19295685	4.53664479	0.65631206	1.71066537	7.36262422
6	6.26530121	6.61556750	-0.35026629	3.93489519	9.29623982
7	6.52209280	4.53664479	1.98544800	1.71066537	7.36262422
8	7.75233516	7.48266933	0.26966583	4.77138092	10.19395774
9	7.16239750	5.65911693	1.50328057	2.59371883	8.72451502
10	6.97447891	6.88606699	0.08841192	3.91806085	9.85407313
11	8.06432196	6.17801676	1.88630520	3.17671916	9.17931435
12	6.81344460	8.32393813	-1.51049353	5.09937011	11.54850614
13	6.30444880	6.61556750	-0.31111870	3.93489519	9.29623982
14	5.43807931	4.53664479	0.90143451	1.71066537	7.36262422
15	7.50108212	6.57887623	0.92220589	3.32962121	9.82813125
16	6.17378610	8.40242863	-2.22864253	5.45205861	11.35279866

TABLE B.7.2-4. TASK 203 PREDICTIONS (Continued)

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SUM OF RESIDUALS	2.81693016
SUM OF SQUARED RESIDUALS	21.88325943
SUM OF SQUARED RESIDUALS - ERROR SS	0.00000000
PRESS STATISTIC	67.32524650
FIRST ORDER AUTOCORRELATION	-0.09949541
DURBIN-WATSON D	1.94472231

TABLE B.7.2-5. TASK 204 FMECA/FMEA

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	276.13316954	92.04438985	68.30	0.0029	0.985569	17.2206
ERROR	3	4.04321133	1.34773711		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	6	280.17638087			1.16092080		6.74145066

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
HC	1	201.56422842	149.56	0.0012	1	3.15523095	2.34	0.2235
LOD	1	30.80230062	22.85	0.0174	1	1.37914387	1.02	0.3862
NOU	1	43.76664050	32.47	0.0107	1	43.76664050	32.47	0.0107

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
HC	1.89703627	1.53	0.2235	1.23983146
LOD	1.31540520	1.01	0.3862	1.30034132
NOU	1.36153998	5.70	0.0107	0.23892489

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	5.18178355	5.02503224	0.15675131	1.37399413	8.67607034
2	7.24992554	6.15389931	1.09602623	2.72448196	9.58311666
3	6.15485809	6.08422800	0.07063009	3.14519169	9.02326431
4	7.93092537	8.00217556	-0.07125019	4.84496502	11.15938611
5	5.75257264	4.69822510	1.05434754	1.15636989	8.24008031
6	8.17863879	9.48081118	-1.30217239	6.17330876	12.78831360

SUM OF RESIDUALS	1.00433259
SUM OF SQUARED RESIDUALS	4.04321133
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	24.05124784
FIRST ORDER AUTOCORRELATION	-0.29775370
DURBIN-WATSON D	2.17004760

TABLE B.7.2-6. TASKS 301 302 303 AND 304 RCL TESTING

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: MNHR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	3	1756941.69816420	585647.23272140	18.11	0.0086	0.931435	38.9330
ERROR	4	129333.30183580	32333.32545895		ROOT MSE		MNHR MEAN
UNCORRECTED TOTAL	7	1886275.00000000			179.81469756		461.85714286

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
NOS	1	1104273.23701894	34.15	0.0043	1	6573.38566420	0.20	0.6754
RQT	1	521897.70600827	16.14	0.0159	1	503114.38845572	15.56	0.0169
PRAT	1	130770.75513699	4.04	0.1147	1	130770.75513699	4.04	0.1147

PARAMETER	ESTIMATE	T FOR H0: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
NOS	3.13064952	0.45	0.6754	6.94328642
RQT	418.68847265	3.94	0.0169	106.14091374
PRAT	239.42465753	2.01	0.1147	119.05256205

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	900.00000000	745.77131675	154.22868325	278.98739970	1212.55523379
2	300.00000000	424.94977169	-124.94977169	-13.11119340	863.01073678
3	269.00000000	245.68595657	23.31404343	-206.17715037	697.54906352
4	318.00000000	481.30146305	-163.30146305	18.08072172	944.52220438
5	654.00000000	437.47236977	216.52763023	7.74296019	867.20177935
6	207.00000000	302.03764794	-95.03764794	-165.37655338	769.45184925
7	585.00000000	667.50507874	-82.50507874	179.91666750	1155.09348999

SUM OF RESIDUALS	-71.72360451
SUM OF SQUARED RESIDUALS	129333.30183580
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000000
PRESS STATISTIC	380124.91994910
FIRST ORDER AUTOCORRELATION	-0.57284247
DURBIN-WATSON D	2.90913661

TABLE B.7.2.7. ALL TASKS ($T_{R/M}$)

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: CTIME

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	6	1075145050.90663000	179190841.81777200	14.61	0.0001	0.845606	67.1667
ERROR	16	196303810.09336900	12268988.13083550		ROOT MSE		CTIME MEAN
UNCORRECTED TOTAL	22	1271448861.00000000			3502.71153977		5214.95454545

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
P101	1	55603928.12047130	4.53	0.0491	1	3319212.91011035	0.27	0.6101
P104	1	995381100.13355900	81.13	0.0001	1	548208981.94627000	44.68	0.0001
P201	1	8945006.02514912	0.73	0.4058	1	3185094.16174193	0.26	0.6173
P203	1	1424576.37541754	0.12	0.7377	1	960356.00166760	0.08	0.7832
P204	1	13507555.04566630	1.10	0.3096	1	13777980.90381580	1.12	0.3050
P301	1	282885.20636817	0.02	0.8812	1	282885.20636817	0.02	0.8812

PARAMETER	ESTIMATE	T FOR HO: PARAMETER=0	PR > |T|	STD ERROR OF ESTIMATE
P101	2.73118985	0.52	0.6101	5.25095997
P104	8.24667729	6.68	0.0001	1.23370209
P201	4.04928139	0.51	0.6173	7.94732900
P203	4.54061840	0.28	0.7832	16.22942938
P204	17.78883553	1.06	0.3050	16.78645937
P301	182.07377341	0.15	0.8812	1199.07582707

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
1	4059.00000000	5081.63686045	-1022.63686045	-1183.54565675	11346.81937765
2	12788.00000000	13868.11429759	-1080.11429759	5855.84914209	21880.37945308
3	6077.00000000	9535.97216045	-3458.97216045	2526.17657933	16545.76774157
4	14271.00000000	11830.74380066	2440.25619934	4600.07491630	19061.41268503
5	19317.00000000	11279.90557068	8037.09442932	4631.89449531	17927.91664605
6	3826.00000000	7692.28438528	-3866.28438528	1037.90454448	14346.66422608
7	6742.00000000	10966.42142620	-4224.42142620	4335.06355381	17597.77929860
8	1216.00000000	1139.62917893	76.37082107	-5874.23527080	8153.49362865
9	3221.00000000	1807.31046275	1413.68953725	-5431.64331864	9046.26424414
10	395.00000000	638.67268918	-243.67268918	-5478.96980431	6756.21518268
11	3241.00000000	2348.28738195	892.71261805	-5161.20840390	9857.78316781
12	1883.00000000	481.71710225	1401.28289775	-5703.07666286	6666.51086736
13	230.00000000	72.64989439	157.35010561	-6059.44980306	6204.74959184
14	1480.00000000	1535.10742432	-55.10742432	-5282.94652780	8353.16137644
15	17673.00000000	11032.52665438	6640.47334562	4405.88131488	17659.17199388
16	6586.00000000	11908.20200388	-5322.20200388	5047.39793729	18769.00607047
17	3564.00000000	3664.50011871	-100.50011871	-4928.85861305	12257.85885047
18	743.00000000	388.26217668	354.73782332	-5758.03345982	6534.55781318
19	480.00000000	290.59957757	189.40042243	-6087.92698087	6669.12613601
20	3159.00000000	4125.82282775	-966.82282775	2455.15444540	10704.80010090
21	665.00000000	1287.52759188	-622.52759188	-5702.62701868	8277.68220245

TABLE B.7.2.7. ALL TASKS ($T_{R/M}$) Continued

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: CTIME

OBSERVATION	OBSERVED VALUE	PREDICTED VALUE	RESIDUAL	LOWER 90% CL INDIVIDUAL	UPPER 90% CL INDIVIDUAL
22	3113.00000000	3237.14875551	-124.14875551	-4286.66657359	10760.96408462

SUM OF RESIDUALS	516.00765855
SUM OF SQUARED RESIDUALS	196303810.09336800
SUM OF SQUARED RESIDUALS - ERROR SS	-0.00000045
PRESS STATISTIC	348052061.64597100
FIRST ORDER AUTOCORRELATION	-0.16651557
DURBIN-WATSON D	2.32762524

B.8 Computer output for STEPWISE

B.8.1 Explanation of Terms.* For each model of a given size, STEPWISE [12] Prints an analysis-of-variance table, the regression coefficients, and related statistics. The analysis-of-variance table includes:

a. The source of variation REGRESSION (1), which is the variation that is attributed to the independent variables in the model the source of variation ERROR (2), which is the residual variation that is not accounted for by the model, and the source of variation TOTAL (3), which is corrected for the mean of y if an intercept is included in the model, uncorrected if an intercept is not included.

b. DF, degrees of freedom (4)

c. SUMS OF SQUARES for REGRESSION, ERROR, and TOTAL (5)

d. MEAN SQUARES for REGRESSION and ERROR (6)

e. The F value (7) which is the ratio of the REGRESSION mean square to the ERROR mean square.

f. PROB > F (8), the significance probability of the F value

g. R SQUARE (9) or R^2, the square of the multiple correlation coefficient.

h. C(P) statistic proposed by Mallows (10) should be near p where p is the number of parameters estimated.

i. The names of the independent variables included in the model (11)

j. B VALUES, the corresponding estimated regression coefficients (12)

k. STD ERROR of the estimates (13)

l. TYPE II SS (sum of squares) for each variable (14), which is the SS that is added to the error SS if that one variable is removed from the model.

m. F values and PROB > F associated with the Type II sums of squares (15).

* [illegible] numbers in parentheses refer to the sample output.

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE [illegible]

STEP 1 VARIABLE NT ENTERED R SQUARE [illegible] C(P) [illegible]

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
ERROR	[illegible]	[illegible]	[illegible]		
TOTAL	[illegible]	[illegible]			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NT	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

THE ABOVE MODEL IS THE BEST 1 VARIABLE MODEL FOUND

STEP 2 VARIABLE RF ENTERED R SQUARE [illegible] C(P) [illegible]

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
ERROR	9	[illegible]	[illegible]		
TOTAL	11	[illegible]			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NT	1.8[illegible]	0.1958[illegible]	[illegible]	[illegible]	[illegible]
RF	1.22750143	0.886[illegible]	[illegible]	[illegible]	[illegible]

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND

STEP 3 VARIABLE DC ENTERED R SQUARE = 0.968687[illegible] C(P) = [illegible]00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	288.17[illegible]	96.[illegible]	[illegible]	0.000[illegible]
ERROR	8	9.31551090	1.1[illegible]		
TOTAL	11	297.49[illegible]			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
DC	0.53200134	0.8008[illegible]	0.51[illegible]	[illegible]	[illegible]
NT	1.70968866	0.27009[illegible]	[illegible]	[illegible]	0.000[illegible]
RF	1.33563076	0.9[illegible]	[illegible]	[illegible]	[illegible]

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND

B.8.2 Output of STEPWISE. Tables B.8.2.1 through B.8.[illegible] [illegible] printouts for STEPWISE.

MAXIMUM R SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MNHR

STEP 1   VARIABLE NT ENTERED   R SQUARE = 0 95991909   C(P) = 1 24015047

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	1	285 56882958	285 56882958	239 50	0 0001
ERROR	10	11 92377316	1 19237732		
TOTAL	11	297 49260274			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NT	2 03637160	0 13158564	285 56882958	239 50	0 0001

THE ABOVE MODEL IS THE BEST 1 VARIABLE MODEL FOUND

STEP 2   VARIABLE RF ENTERED   R SQUARE = 0 96696011   C(P) = 1 44126176

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	287 66348053	143 83174026	131 70	0 0001
ERROR	9	9 82912221	1 09212469		
TOTAL	11	297 49260274			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NT	1 82859962	0 19587472	95 18150854	87 15	0 0001
RF	1 22750143	0 88634396	2 09465095	1 92	0 1994

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND

STEP 3   VARIABLE DC ENTERED   R SQUARE = 0 96868725   C(P) = 3 00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	288 17729184	96 05909728	82 50	0 0001
ERROR	8	9 31531090	1 16441386		
TOTAL	11	297 49260274			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
DC	0 57200134	0 80087471	0 51381131	0 44	0 5252
NT	1 70968866	0 27009334	46 65666281	40 07	0 0002
RF	1 33563076	0 92957114	2 40389183	2 06	0 1887

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND

TABLE B.8.2-2. TASKS 104 AND 105 FRACAS FRB

MAXIMUM R SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MNHR

THE FIRST 1 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES

STEP 0   INCLUDED VARIABLE ENTERED   R SQUARE = 0.83195083   C(P) = 264.97549634

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	1	695.16532843	695.16532843	54.46	0.0001
ERROR	11	140.41930107	12.76539101		
TOTAL	12	835.58462951			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	9.07715545	1.23005005	695.16532843	54.46	0.0001

STEP 2   VARIABLE DOI ENTERED   R SQUARE = 0.99363336   C(P) = 2.41760493

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	830.26476347	415.13238174	780.34	0.0001
ERROR	10	5.31986604	0.53198660		
TOTAL	12	835.58462951			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	0.25081239	0.60812911	0.09049136	0.17	0.6887
DOI	2.49622831	0.15664502	135.09943504	253.95	0.0001

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND.

STEP 3   VARIABLE ANU ENTERED   R SQUARE = 0.99449972   C(P) = 3.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	830.98867923	276.99622641	542.43	0.0001
ERROR	9	4.59595028	0.51066114		
TOTAL	12	835.58462951			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	0.80975425	0.75853753	0.58194929	1.14	0.3135
DOI	2.27880335	0.23857262	46.59135103	91.24	0.0001
ANU	0.22134263	0.18590346	0.72391575	1.42	0.2643

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND.

TABLE B.8.2-3. TASKS 201 AND 202 MODELING/ALLOCATIONS

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MMHR

THE FIRST 1 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES.

STEP 0 INCLUDED VARIABLE ENTERED R SQUARE = 0.51437487 C(P) = 42.53996867

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	1	107.87490243	107.87490243	7.41	0.0296
ERROR	7	101.84549574	14.54935653		
TOTAL	8	209.72039817			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
MAC	7.05415656	2.59063828	107.87490243	7.41	0.0296

STEP 2 VARIABLE NOU ENTERED R SQUARE = 0.93505586 C(P) = 2.49139859

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	196.10028828	98.05014414	43.19	0.0003
ERROR	6	13.62010989	2.27001832		
TOTAL	8	209.72039817			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
MAC	4.35037838	1.11140530	34.78071438	15.32	0.0079
NOU	0.86574489	0.13886981	88.22538585	38.87	0.0008

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND.

STEP 3 VARIABLE RC ENTERED R SQUARE = 0.94997678 C(P) = 3.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	199.22950803	66.40983601	31.65	0.0011
ERROR	5	10.49089014	2.09817803		
TOTAL	8	209.72039817			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
MAC	2.03085368	2.17926556	1.82212973	0.87	0.3942
RC	2.07132859	1.69610266	3.12921975	1.49	0.2764
NOU	0.79822657	0.14450481	64.02212590	30.51	0.0027

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND.

[illegible]

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MNHR

THE FIRST 2 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES

STEP 0 INCLUDED VARIABLES ENTERED R SQUARE = 0 85440186 C(P) = 42 53362306

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	636 63431860	318 31715930	41 08	0 0001
ERROR	14	108 48849283	7 74917806		
TOTAL	16	745 12281143			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	1 68558901	1 80916178	6 72673341	0 87	0 3673
LOD	5 81287792	1 51097990	114 68871052	14 80	0 0018

STEP 3 VARIABLE RF ENTERED R SQUARE = 0 94687549 C(P) = 9 89772805

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	705 53852553	235 17950851	77 24	0 0001
ERROR	13	39 58428590	3 04494507		
TOTAL	16	745 12281143			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	1 12459306	1 14018383	2 96224182	0 97	0 3420
LOD	3 28522661	1 08601928	27 86346097	9 15	0 0098
RF	5 16358377	1 08547066	68 90420693	22 63	0 0004

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND

STEP 4 VARIABLE POC ENTERED R SQUARE = 0 96265401 C(P) = 5 98789866

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	4	717 29546460	179 32386615	77 33	0 0001
ERROR	12	27 82734684	2 31894557		
TOTAL	16	745 12281143			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	1 30838913	0 99835938	3 98281928	1 72	0 2145
LOD	2 46888312	1 01472732	13 72754599	5 92	0 0316
RF	3 34290943	1 24544926	16 70658612	7 20	0 0199
POC	1 48865466	0 66113798	11 75693907	5 07	0 0439

TABLE D-8 ... TASK 205 PREDICTIONS (Continued)

MAXIMUM R SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MNHR

THE FIRST 2 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES

STEP 4 RF REPLACED BY RNR R SQUARE = 0.96630114 C(P) = 4.62187166

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	4	720.01302126	180.00325531	86.02	0.0001
ERROR	12	25.10979018	2.09248251		
TOTAL	16	745.12281143			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	0.78581829	0.98300379	1.33719802	0.64	0.4396
LOD	2.10251540	0.98320450	9.56869200	4.57	0.0537
POC	1.64288682	0.57916806	16.83712450	8.05	0.0150
RNR	2.07556758	0.68123486	19.42414278	9.28	0.0101

THE ABOVE MODEL IS THE BEST 4 VARIABLE MODEL FOUND.

STEP 5 VARIABLE RF ENTERED R SQUARE = 0.97063134 C(P) = 5.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	5	723.23955200	144.64791040	72.71	0.0001
ERROR	11	21.88325943	1.98938722		
TOTAL	16	745.12281143			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	0.84071524	0.96028450	1.59822702	0.80	0.3893
LOD	2.13853624	0.95909479	9.89075595	4.97	0.0475
RF	1.83975538	1.44461407	3.22653075	1.62	0.2291
POC	1.31541501	0.62050682	8.94029367	4.49	0.0576
RNR	1.43787113	0.83183470	5.94408740	2.99	0.1118

THE ABOVE MODEL IS THE BEST 5 VARIABLE MODEL FOUND.

TABLE B.8.2-5. TASK 204 FMECA FMEA

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE MNHR

STEP 1 VARIABLE NOU ENTERED R SQUARE = 0.94504143 C(P) = 7.42514645

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	1	264.77828700	264.77828700	85.98	0.0002
ERROR	5	15.39809387	3.07961877		
TOTAL	6	280.17638087			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NOU	1.89875056	0.20477419	264.77828700	85.98	0.0002

THE ABOVE MODEL IS THE BEST 1 VARIABLE MODEL FOUND.

STEP 2 VARIABLE HC ENTERED R SQUARE = 0.98064664 C(P) = 2.02330333

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	274.75402567	137.37701283	101.34	0.0004
ERROR	4	5.42235521	1.35558880		
TOTAL	6	280.17638087			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	2.66559558	0.98262026	9.97573867	7.36	0.0534
NOU	1.49025273	0.20281433	73.18979724	53.99	0.0018

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND.

STEP 3 VARIABLE LOD ENTERED R SQUARE = 0.98556905 C(P) = 3.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	276.13316954	92.04438985	68.30	0.0029
ERROR	3	4.04321133	1.34773711		
TOTAL	6	280.17638087			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	1.89703627	1.23983146	3.15523095	2.34	0.2235
LOD	1.31540520	1.30034132	1.37914387	1.02	0.3862
NOU	1.36153998	0.23892489	43.76664050	32.47	0.0107

THE ABOVE MODEL IS THE BEST 3 VARIABLE MODEL FOUND.

TABLE B.8.2-6. TASKS 301 302 303 AND 304 REL TESTING

MAXIMUM R SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE HRS

STEP 1 VARIABLE HC ENTERED R SQUARE = 0.90488672 C(P) = 1.14543570

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	1	1706865.19047619	1706865.19047619	57.08	0.0003
ERROR	6	179409.80952381	29901.63492063		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	285.09523810	37.73443225	1706865.19047619	57.08	0.0003

THE ABOVE MODEL IS THE BEST 1 VARIABLE MODEL FOUND.

STEP 2 VARIABLE RQT ENTERED R SQUARE = 0.92183474 C(P) = 2.05039391

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	1738833.83333333	869416.91666667	29.48	0.0017
ERROR	5	147441.16666667	29488.23333333		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
HC	213.41666667	78.37972917	218624.03333333	7.41	0.0416
RQT	167.25000000	160.63064517	31968.64285714	1.08	0.3455

STEP 2 HC REPLACED BY PRAT R SQUARE = 0.92794970 C(P) = 1.65529622

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	1750368.31250000	875184.15625000	32.20	0.0014
ERROR	5	135906.68750000	27181.33750000		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
RQT	444.12500000	82.43381815	788988.06250000	29.03	0.0030
PRAT	268.18750000	92.16381052	230158.51250000	8.47	0.0334

THE ABOVE MODEL IS THE BEST 2 VARIABLE MODEL FOUND.

TABLE B.8.2-6. TASKS 301 302 303 AND 304 REL TESTING (Continued)

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE HRS

THE FIRST 3 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES.

STEP 0 INCLUDED VARIABLES ENTERED R SQUARE = 0.93143455 C(P) = 3.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	1756941.69816420	585647.23272140	18.11	0.0086
ERROR	4	129333.30183580	32333.32545895		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
NCS	3.13064952	6.94328642	6573.38566420	0.20	0.6754
RQT	418.68847265	106.14091374	503114.38845572	15.56	0.0169
PRAT	239.42465753	119.05256205	130770.75513699	4.04	0.1147

[illegible] TASKS 301 302 303 AND 304 REL TESTING (Continued)

MAXIMUM R SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE HRS

STEP [illegible] VARIABLE HC ENTERED R SQUARE = 0.95356819 C(P) = 2.00004064

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	1798691.83333333	599563.94444444	27.38	0.0040
ERROR	4	87583.16666667	21895.79166667		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
[illegible]	126.91666667	85.43182792	48323.52083333	2.21	0.2116
[illegible]	253.75000000	147.97226655	64389.06250000	2.94	0.1615
[illegible]	173.00000000	104.63219310	59858.00000000	2.73	0.1736

[illegible] IS THE BEST [illegible] VARIABLE MODEL FOUND.

STEP [illegible] VARIABLE [illegible] ENTERED R SQUARE = 0.95356882 C(P) = 4.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	4	1798693.01963615	449673.25490904	15.40	0.0243
ERROR	3	87581.98036385	29193.99345462		
TOTAL	7	1886275.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
[illegible]	127.16979498	106.33974421	41751.32147196	1.43	0.3176
[illegible]	0.04533641	7.11207180	1.18630282	0.00	0.9953
[illegible]	253.75866590	170.87174957	64376.33941094	2.21	0.2342
[illegible]	173.22668207	125.94258954	55230.35606985	1.89	0.2627

[illegible] IS THE BEST 4 VARIABLE MODEL FOUND.

TABLE B.8.2.7. ALL TASKS ($T_{R/M}$)

MAXIMUM R-SQUARE IMPROVEMENT FOR DEPENDENT VARIABLE CTIME

THE FIRST 6 VARIABLES IN EACH MODEL ARE INCLUDED VARIABLES.

STEP 0 INCLUDED VARIABLES ENTERED R SQUARE = 0.84560621 C(P) = 6.00000000

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	6	1075145050.90663000	179190841.81777200	14.61	0.0001
ERROR	16	196303810.09336800	12268988.13083550		
TOTAL	22	1271448861.00000000			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
P1'1	2.75118985	5.25095997	3319212.91011036	0.27	0.6101
P1[illegible]	8.24667729	1.23370209	548208981.94627000	44.68	0.0001
P.01	6.04928159	7.94732900	3185094.16174192	0.26	0.6173
P.05	4.54061840	16.22942938	960356.00166758	0.08	0.7832
P.[illegible]	17.78885555	16.78645937	13777980.90381580	1.12	0.3050
P501	182.07377341	1199.07582707	282885.20636818	0.02	0.8812

BOUNDS ON CONDITION NUMBER 3.028083, 137.6404

END

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